

CRANFIELD UNIVERSITY

TOBILOBA ELUSAKIN

ADVANCED RELIABILITY ANALYSIS OF COMPLEX OFFSHORE
ENERGY SYSTEMS SUBJECT TO CONDITION BASED
MAINTENANCE

SCHOOL OF WATER, ENERGY AND ENVIRONMENT
PhD in Energy and Power

PhD
Academic Year: 2020 - 2021

Supervisor: Professor Nigel Simms
Associate Supervisor: Dr Mahmoud Shafiee
April 2021

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the degree of PhD

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ABSTRACT

As the demand for energy in our world today continues to increase and conventional reserves become less available, energy companies find themselves moving further offshore and into more remote locations for the promise of higher recoverable reserves. This has been accompanied by increased technical, safety and economic risks as the unpredictable and dynamic conditions provide a challenge for the reliable and safe operation of both oil and gas (O&G) and offshore wind energy assets. Condition-based maintenance (CBM) is growing in popularity and application in offshore energy production, and its integration into the reliability analysis process allows for more accurate representation of system performance. Advanced reliability analysis while taking condition-based maintenance (CBM) into account can be employed by researchers and practitioners to develop a better understanding of complex system behaviour in order to improve reliability allocation as well as operation and maintenance (O&M). The aim of this study is therefore to develop models for reliability analysis which take into account dynamic offshore conditions as well as condition-based maintenance (CBM) for improved reliability and O&M.

To achieve this aim, models based on the stochastic petri net (SPN) and dynamic Bayesian network (DBN) techniques are developed to analyse the reliability and optimise the O&M of complex offshore energy assets. These models are built to take into account the non-binary nature, maintenance regime and repairability of most offshore energy systems. The models are then tested using benchmark case studies such as a subsea blowout preventer, a floating offshore wind turbine (FOWT), an offshore wind turbine (OWT) gearbox and an OWT monopile. Results from these analyses reveal that the incorporation of degradation and CBM can indeed be done and significantly influence the reliability analysis and O&M planning of offshore energy assets.

Keywords:

Reliability, operation and maintenance, condition monitoring, Bayesian networks, Petri nets, Offshore energy

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LIST OF ABBREVIATIONS

AIM	Asset Integrity Management
AHP	Analytical Hierarchy Process
API	American Petroleum Institute
BAST	Best Available and Safest Technology
BBN	Bayesian Belief Network
BCR	Benefit Cost Ratio
BN	Bayesian Network
BOEM	Bureau of Ocean Energy Management
BOP	Blowout Preventer
BSEE	Bureau of Safety, Energy and Environment
BSI	British Standards Institute
CAPEX	Capital Expenditure
CBM	Condition-based Maintenance
CM	Corrective Maintenance
CMS	Condition Monitoring System
CPM	Condition and Performance Monitoring
CPN	Cost Priority Number
CPT	Conditional Probability Table
DAG	Directed Acyclic Graph
DBN	Dynamic Bayesian Network
DOOBN	Dynamic Object-Oriented Bayesian Network
DSPN	Deterministic and Stochastic Petri Net
EDS	Emergency Disconnect System
ELECTRE	Elimination Et Choix Traduisant la Realite
ETA	Event Tree Analysis
EWS	Electronic Workstation
FCI	Failure Criticality Index
FMEA	Failure Mode and Effect Analysis
FMECA	Failure Mode Effect and Criticality Analysis
FORM	First Order Reliability Method
FOWT	Floating Offshore Wind Turbine
GUI	Graphical User Interface

HAZID	Hazard Identification
HAZOP	Hazard and Operability
HIL	Hardware in the Loop
HPHT	High Pressure High Temperature
ID	Influence Diagram
IO	Integrated Operations
IRR	Internal Rate of Returns
KPI	Key Performance Indicator
LCOE	Levelised Cost of Energy
LMRP	Lower Marine Riser Package
MCDM	Multi Criteria Decision Making
MCMC	Markov Chain Monte Carlo
MCS	Monte Carlo Simulation
MLE	Maximum Likelihood Estimator
MMS	Mineral Management Service
MTBF	Mean Time Between Failures
MTTF	Mean Time to Failure
MUX	Multiplex Electro-Hydraulic
NDT	Non-Destructive Testing
NOV	National Oilwell Varco
NPV	Net Present Value
NREL	National Renewable Energy Laboratory
O&M	Operation and Maintenance
OC3	Offshore Code Comparison Collaboration
OCS	Outer Continental Shelf
OOBN	Object Oriented Bayesian Network (OOBN)
OPEX	Operational Expenditure
OWT	Offshore Wind Turbine
PM	Preventive Maintenance
PN	Petri Net
RAM	Reliability Availability and Maintainability
RI	Reliability Importance
RIF	Risk Influencing Factor

ROV	Remote Operating Vehicle
RPN	Risk Priority Number
RSM	Response Surface Method
RUL	Remaining Useful Life
SCADA	Supervisory Control and Data Acquisition
SDS	Subsea Deployment System
SHM	Structural Health Monitoring
SID	Subsea Isolation Device
SINTEF	Foundation for Scientific and Industrial Research
SIS	Safety Instrumented Systems
SORM	Second Order Reliability Method
SPN	Stochastic Petri Nets
SS	Subset Simulation
SVM	Support Vector Machine
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
UT	Ultrasonic Testing

1 INTRODUCTION

1.1 Research Background

As the demand for energy in our world today steadily increases, stakeholders in the energy industries are having to meet this demand through reserves located in remote areas, i.e., offshore. This is because these locations are known to hold the promise of significantly higher resources. This shift towards the offshore environment, however, presents several additional challenges which inherently compromise asset safety, reliability and operation and maintenance (O&M). These challenges arise as a result of the harsher environmental conditions as well as rapid changes in operational conditions. Furthermore, this shift towards the offshore environment requires that equipment developed to harness these resources are able to function as needed in harsher conditions. This performance requirement therefore necessitates a better understanding of the reliability of offshore energy assets. In order to address these challenges, energy companies are now leaning towards asset integrity management (AIM) systems, which work to ensure that resources, systems and people delivering integrity are all in place and will perform their intended functions when required over the asset's lifecycle (HSE, 2007).

The reliability of any modern industrial system is a fundamental characteristic that ensures its safe and dependable operation. Reliability analysis is performed to quantify the probability of failure of any system and the barriers which have been developed for its protection (Zio, 2009). Within the lifecycle of modern complex systems, the process of reliability analysis can occur during the concept definition, design, development and maintenance phases in order to estimate the dependability of the system (Alvares Tejedor *et al.*, 2013).

Modern reliability analysis of complex systems dates back to the early 1960s with the use of fault tree analysis (FTA) to study Missile Launch Control Systems (Lee *et al.*, 1985). Over the years and with the advancement of technology, the process of reliability analysis has evolved to more accurately understand the performance of complex systems with other conventional techniques such as failure mode and

effect analysis (FMEA), reliability block diagrams (RBD) and event tree analysis (ETA) being developed (Rausand and Hoyland, 2004).

While these conventional techniques do well to help operators and asset managers better understand the behaviour of complex offshore energy systems, they often simplify the reliability analysis process by making assumptions regarding system behaviour (Kabir and Papadopoulos, 2019). These assumptions include having a single mode of operation, non-repairability of systems and binary states of components or subsystems (i.e., working and failed). In reality however, these assumptions are invalid as offshore energy systems frequently operate in multiple modes, experience faults or failures multiple times during their operational lifetime, and possess intermediate states between working and failed. In order to overcome the limitations presented by conventional techniques, advanced techniques such as Petri Nets (PN), Markov models (MM), Monte Carlo Simulation (MCS) and Bayesian networks (BN) have been developed (Shafiee *et al.*, 2020).

The promotion of AIM in offshore energy companies has also brought about the increasing adoption of sensors and monitoring data and by extension, condition-based maintenance (CBM) (Rahim *et al.*, 2010). CBM is a subset of preventive maintenance (PM) which involves maintenance decisions made on the basis of an asset's condition. In this strategy, actions are performed when the asset reaches the level defined as critical by operators (Bengtsson, 2004). Compared to time-based maintenance (TBM), another subset of PM, and corrective maintenance, CBM provides the most suitable and economical approach to observe and analyse the gradual degradation of system performance, especially in harsh offshore environments (Gugaliya and Naikan, 2019).

Nevertheless, there are outstanding questions in relation to the robust reliability analysis and O&M planning for complex multi-component systems while taking the aforementioned assumptions as well as the prevalent maintenance regime (in this case, CBM) into account. There are also limited solutions dedicated to the application of CBM in offshore energy operations and its influence on improved production, reduced O&M costs, and better reliability of offshore energy assets.

1.2 Research Development

This thesis focuses on the application of two advanced techniques for reliability and O&M analysis: Bayesian networks and Petri nets. To decide on these two techniques, literature reviews were conducted on reliability analysis techniques applied towards the offshore energy assets chosen for this thesis (seen in chapters 4 and 5 respectively). From these reviews, it was found that the application of the Petri Net and Bayesian Network techniques had not been explored in-depth as compared to other reliability analysis techniques. Furthermore, both the BN and PN techniques were found to possess the ability to model changes in the behaviour of systems over time and incorporate the maintenance regime of the system into the reliability analysis process. Both techniques also employ a graphical approach in addition to data analytics making them more attractive to asset management professionals in industry.

This thesis focuses on the two major offshore energy industries for its application cases: oil and gas (O&G) and wind-based renewables. For offshore oil and gas, the subsea blowout preventer (BOP) has been chosen for this research due to its reputation as one of the most critical safety instrumented systems (SISs) when compared to other offshore O&G exploration assets. The BOP is considered the last line of defence against erratic well pressures and possible well blowouts, preventing failures that could result in significant loss of life, catastrophic economic losses, and considerable environmental damage (Shafiee *et al.*, 2020). This, in addition to the recent gradual shift in exploration towards deeper waters and tougher environmental conditions, has ensured that the reliability of the subsea BOP remains of paramount importance to industry stakeholders.

In offshore renewable energy, the offshore wind turbine (OWT) has been selected as the asset of focus over others due to the increasing popularity and adoption of offshore wind energy over the past decade. In Europe, offshore wind capacity has grown by more than 1200% from 2.9GW in 2010 to 22GW in 2019 (European Wind Energy Association, 2011; Wind Europe, 2020). Furthermore, key components of the OWT which have been addressed in this thesis, i.e., the gearbox and monopile, are considered to be significantly safety/mission-critical

and expensive to maintain/replace. Ultimately, the challenges to wind turbine reliability presented by the offshore environment as well as the high difficulty and cost of O&M remain areas of particular concern to wind energy developers and operators (Adedipe and Shafiee, 2020).

1.3 Aim and Objectives

The aim of this research is to develop advanced reliability analytics for the analysis of critical offshore energy assets operating in dynamic conditions and under condition-based maintenance regimes, in order to improve their overall reliability as well as their operation and maintenance.

To achieve this aim, the following objectives have been outlined:

1. To evaluate and review existing research on reliability assessment of offshore energy assets focusing on:
 - i. Reliability of complex offshore energy systems.
 - ii. Reliability analysis techniques encompassing both conventional and advanced methods.
 - iii. Adopted maintenance regimes, including corrective and preventive maintenance, with a particular focus on CBM.
2. To develop a framework for the effective and efficient implementation of CBM in offshore energy assets.
3. To develop analytical reliability models for offshore energy assets operating under condition-based maintenance in order to improve reliability allocation using advanced reliability analysis techniques.
4. To develop integrated models for optimising operation and maintenance of offshore energy assets operating under condition-based maintenance.
5. To evaluate the developed asset reliability and O&M models using benchmark case studies in offshore oil and gas and wind energy.

Figure 1.1 shows the publication outputs of this thesis and how they are connected to the objectives of the thesis.

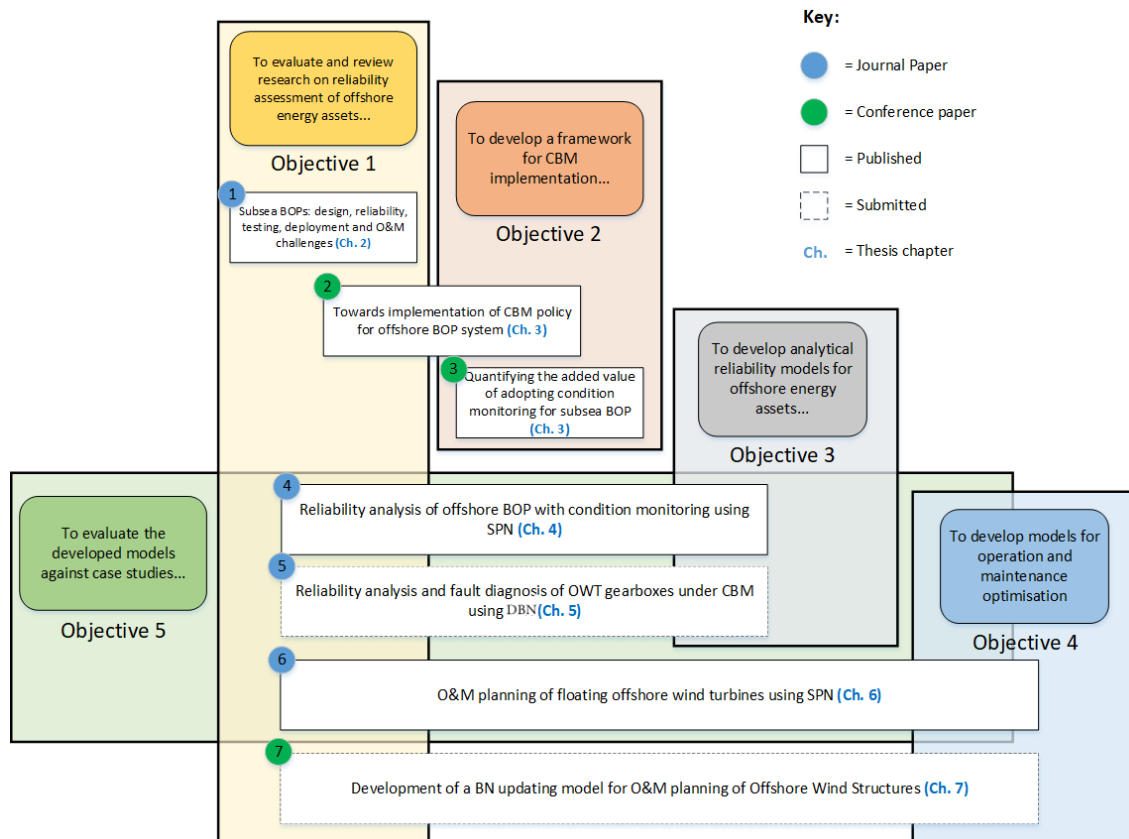


Figure 1.1 Publications resulting from this PhD thesis

1.4 Thesis Plan

This thesis contains seven research papers which have been formatted into six chapters. All papers have been written by the primary author, Tobiloba Elusakin and edited by Dr Mahmoud Shafiee and Professor Nigel Simms with the exception of the subsea BOP review in chapter 2, the primary author of which is Dr Mahmoud Shafiee. This research was performed in conjunction with Dr Mahmoud Shafiee and Dr Evenje Enjema, a former student of Cranfield University. This thesis is divided into four clusters.

The first cluster, containing chapter 2 (paper 1), reviews the challenges associated with the design, reliability, testing, operation and maintenance of subsea blowout preventers. The literature reviewed has been classified

according to two frameworks – the water depths in which the BOPs operate (shallow and deep water), and the reliability analysis techniques applied. The review analysis gave insights into which aspect of BOP operation received the most attention and which received the least, the effect of the Macondo disaster on subsea BOP research, and the reliability analysis techniques which have been applied to subsea BOPs (Chapter 2, **Paper 1 – published:** Shafiee, M., Elusakin, T., Enjema, E. (2020) Subsea blowout preventer (BOP): Design, reliability, testing, deployment, and operation and maintenance challenges. *Journal of Loss Prevention in the Process Industries*, vol. 66).

In order to develop effective models for reliability analysis which incorporate CBM, it is of paramount importance to explore how CBM can be effectively implemented. The second cluster, containing chapter 3 (papers 2 and 3), therefore explores the implementation of condition monitoring and condition-based maintenance (CBM) in offshore energy production and its influence on improved production, reduced operation and maintenance (O&M) costs and improved safety. Chapter 3 details the proposal of a V model-based architecture for implementing CBM policy in offshore systems with a specific focus on subsea blowout preventers (BOPs). The proposed model identified gaps in the implementation for which hardware, software and training requirements were outlined in detail. The first step in the proposed V-model for implementing the CBM policy was then studied further. A framework for performing an economic feasibility analysis of implementing CMS in subsea oil and gas production systems, with a particular focus on blowout preventers (BOP) was presented. The analysis performed applied the net present value (NPV) and benefit cost ratio (BCR) techniques on the implementation of a real-life CMS, with results indicating viability in both metrics. The findings indicated that the proposed approach could provide asset managers and maintenance professionals with a key decision-making tool to make an informed case for implementing CBM (**Paper 2 – published:** Elusakin, T., Shafiee, M., Adedipe, T. (2019) Towards Implementing Condition-based Maintenance (CBM) Policy for Offshore Blowout Preventer (BOP) System. In: *Proceedings of the 38th International Conference on Ocean, Offshore and Arctic Engineering*; **Paper 3 – published:** Elusakin, T. and Shafiee,

M. (2020) Quantifying the Added Value of Adopting Condition Monitoring to Subsea Blowout Preventers. *Proceedings of the 30th European Safety and Reliability Conference and 15th Probabilistic Safety Assessment and Management Conference*).

Figure 1.2 shows the logical flow which links the contributions of all chapters in this thesis.

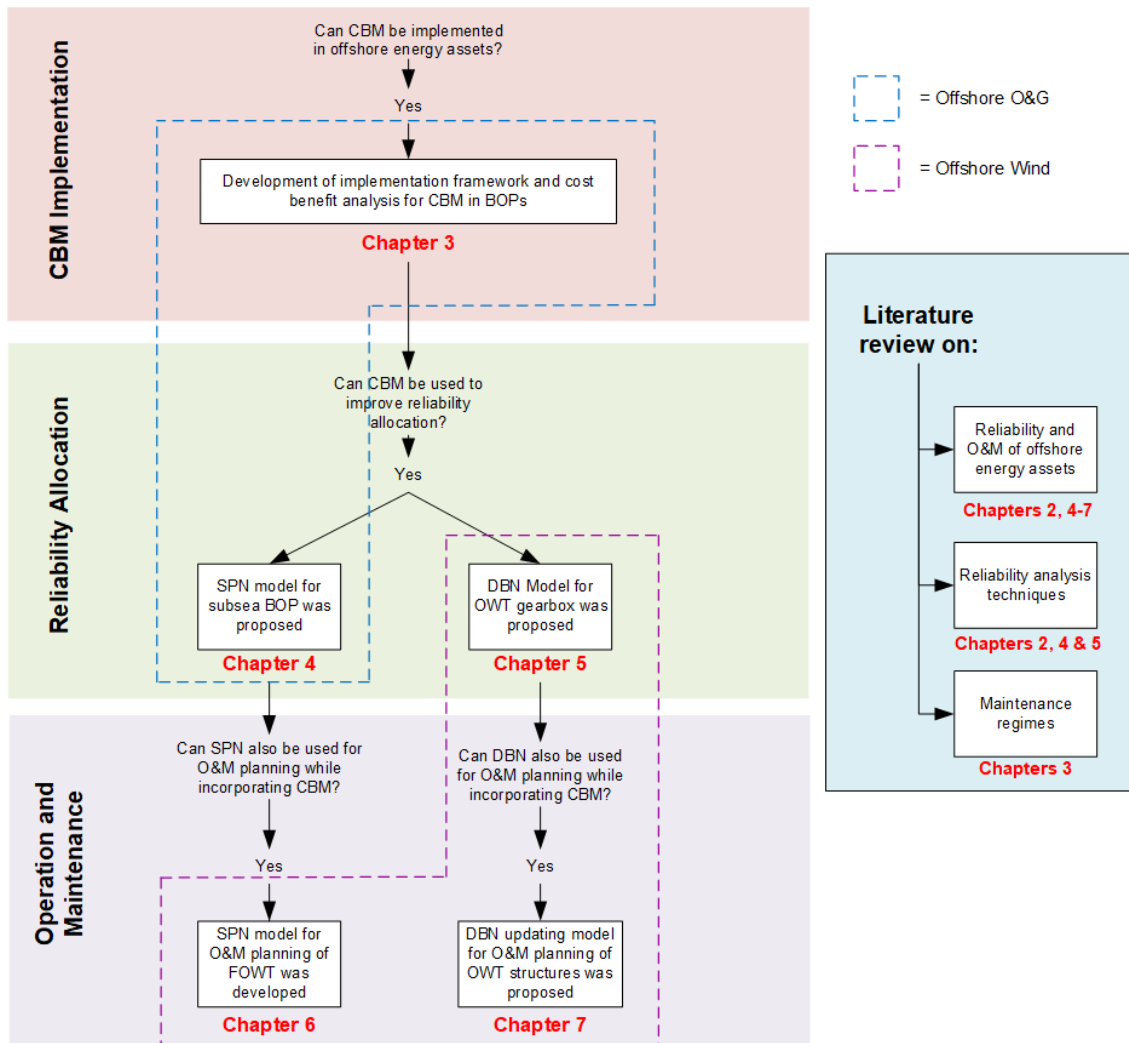


Figure 1.2 Logical flow linking all chapters in the thesis

The third cluster, containing chapters 4 and 5, addresses the development of Stochastic Petri Net (SPN) and Dynamic Bayesian Network (DBN) models for the reliability analysis of complex offshore systems with two cases in the offshore oil and gas (subsea BOP) and offshore wind industry (OWT gearbox) respectively.

Chapter 4 details the development of a model for advanced reliability analysis of subsea BOPs subject to condition-based maintenance (CBM) with multiple failure modes. The reliability, availability and mean time between failures (MTBF) of the BOP system were obtained and analysed (Chapter 4, **Paper 4 – published:** Elusakin, T., and Shafiee, M. (2020) Reliability Analysis of Subsea Blowout Preventers with Condition-based Maintenance (CBM) using Stochastic Petri Nets (SPN). *Journal of Loss Prevention in the Process Industries*, vol 63). Chapter 5 discusses the development of a DBN model for reliability analysis and fault diagnosis of an OWT gearbox. The reliability and mean time between failures (MTBF) of the gearbox assembly were determined and fault diagnosis performed to determine the most likely cause of failure, while taking condition-based maintenance into account (Chapter 5, **Paper 5:** Submitted – Elusakin, T., Shafiee, M., Simms, N., and Adedipe, T. Development of a Dynamic Bayesian Network Model for Reliability Analysis and Fault Diagnosis of Offshore Wind Turbine Gearbox. *Journal of Risk and Reliability*).

The O&M analysis of offshore energy systems was conducted using both the SPN and DBN techniques in the fourth cluster which contains chapters 6 and 7 (papers 6 and 7). Chapter 6 details the application of the SPN technique toward the O&M analysis of floating offshore wind turbines (FOWT). In this study, a Petri Net-based model for O&M analysis which takes into account the degradation, maintenance and condition monitoring process for FOWT components was developed. This serves to provide a better understanding of how the dynamic conditions can be taken into account in analysing the performance of complex offshore assets (Chapter 6, **Paper 6 – published:** Elusakin, T., Shafiee, M., and Adedipe, T. (2021) Operation and Maintenance Planning of Floating Offshore Wind Turbines using Stochastic Petri Net. *Energies* 14(4)). In chapter 7, the DBN technique is applied to model the deterioration of fatigue-based cracks in offshore structures, with a specific focus on OWT monopiles. Here, a novel Bayesian Network updating model which incorporates continuous observations from a remote condition monitoring system (CMS) was proposed, showing that updating the crack size based on near real-time observations is possible, but limited to small time durations due to the requirement of excessive computing power

(Chapter 7, **Paper 7**: Submitted – Elusakin, T. and Shafiee, M. Development of a Bayesian Network Updating Model for O&M planning of Offshore Wind Structures. *EERA DeepWind 2021*).

In chapter 8, the overall implications of the work done in the thesis are discussed.

Finally, chapter 9 presents the key conclusions from this research and provides recommendations for further research and analysis into reliability analysis of offshore energy systems.

Table 1.1 presents the thesis plan and shows the status of the papers included in the thesis.

Table 1.1 Thesis Plan

Chapter	Paper	Objective	Title	Journal/Conference	Status
1	--	1,2,3,4,5	Introduction	--	--
2	1	1	Subsea blowout preventers: design, reliability, testing, deployment, and operation and maintenance challenges	<i>Journal of loss prevention in the process industries</i>	Published
3	2	1,2	Towards implementation of condition-based maintenance (CBM) policy for offshore blowout preventer (BOP) system	<i>Proceedings of the ASME 2019 38th International Conference on Ocean, Offshore and Arctic Engineering</i>	Presented & Published
3	3	1,2	Quantifying the added value of adopting condition monitoring for subsea blowout preventers (BOP)	<i>Proceedings of the 30th European Safety and Reliability Conference and 15th Probabilistic Safety Assessment and Management Conference</i>	Presented and Published
4	4	1,3,5	Reliability analysis of subsea blowout preventers with condition monitoring using	<i>Journal of Loss Prevention in the Process Industries</i>	Published

			stochastic petri nets		
5	5	1,3,5	Reliability analysis and fault diagnosis of offshore wind turbine gearboxes under condition-based maintenance using dynamic Bayesian networks	<i>Journal of Risk and Reliability</i>	Submitted and Under Review
6	6	1,4,5	Operation and maintenance planning of floating offshore wind turbines (FOWT) using stochastic petri nets	<i>Energies</i>	Published
7	7	1,4	Decision support for fatigue-based crack growth management of offshore wind turbine monopiles using dynamic Bayesian networks	<i>EERA DeepWind 2021</i>	Abstract Accepted + Full paper under review
8	--	1,2,3,4,5	Synthesis and Discussion	--	--
9	--	--	Conclusion and Recommendation for further work	--	--

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2 SUBSEA BLOWOUT PREVENTER: DESIGN, RELIABILITY, TESTING, DEPLOYMENT, AND OPERATION AND MAINTENANCE CHALLENGES

Mahmoud Shafiee, Tobiloba Elusakin, Evenje Enjema

Statement of contributions:

Mahmood Shafiee was responsible for conceptualization, methodology, formal analysis, investigation, data curation, writing of the original draft, review & editing, visualization and supervision. Tobiloba Elusakin was responsible for conceptualization, methodology, formal analysis, investigation, data curation, writing of the original draft, review & editing, visualization, and project administration. Evenye Enjema was responsible for conceptualization, methodology, formal analysis, investigation, data curation, writing of the original draft, visualization and project administration.

Abstract

Subsea blowout preventer (BOP) is a safety-related instrumented system that is used in underwater oil drilling to prevent the well to blowout. As oil and gas exploration moves into deeper waters and harsher environments, the setbacks related to reliable functioning of the BOP system and its subsystems remain a major concern for researchers and practitioners. This study aims to systematically review the current state-of-the-art and present a detailed description about some of the recently developed methodologies for through-life management of the BOP system. Challenges associated with the system design, reliability analysis, testing, deployment as well as operability and maintainability are explored, and then the areas requiring further research and development will be identified. A total of 87 documents published since 1980's are critically reviewed and classified according to two proposed frameworks. The first framework categorises the literature based on the depth of water in which the BOP systems operate, with a sub-categorization based on the Macondo disaster. The second framework categorises the literature based on the techniques applied for the reliability analysis of BOP systems, including Failure Mode and Effects Analysis (FMEA),

Fault Tree Analysis (FTA), Reliability Block Diagram (RBD), Petri Net (PN), Markov modelling, Bayesian Network (BN), Monte Carlo Simulation (MCS), etc. Our review analysis reveals that the reliability analysis and testing of BOP has received the most attention (63%) in the literature, whereas the design, deployment, and operation and maintenance (O&M) of BOPs received the least (37%).

2.1 Introduction

In the process of drilling a well for oil and gas, the wellbore is usually lined with a casing through which a drill string runs. The annular (ring-shaped) region between the casing and the drill stem is filled with drilling mud which provides hydrostatic pressure to restrict formation fluids (oil/gas) from coming up the wellbore. When a drill bit punctures a hydrocarbon reservoir, underground pressure forces formation fluids into the wellbore. Throughout the drilling process, these fluids try to force their way through the annulus. Primary well control during drilling is achieved through a counterbalance of reservoir pressure by hydrostatic mud pressure. The appropriate safety margin is achieved by varying the fluid density. When this pressure is lost during a kick, the Blowout Preventer (BOP) is employed as an alternative.

As a large specialized, mechanical array of valves, assembled to seal wells against kicks or blowouts during drilling or work-over operations, a typical BOP consists of Lower Marine Riser Package (LMRP) and a combination of several types of preventers, differing in number and capacity principally for operational reasons. Figure 2.1 shows the conventional and modern BOP systems with their main components including: connectors (wellhead and LMRP), BOP control system, flex joint, annular preventer (upper and lower), ram preventers, choke and kill system.

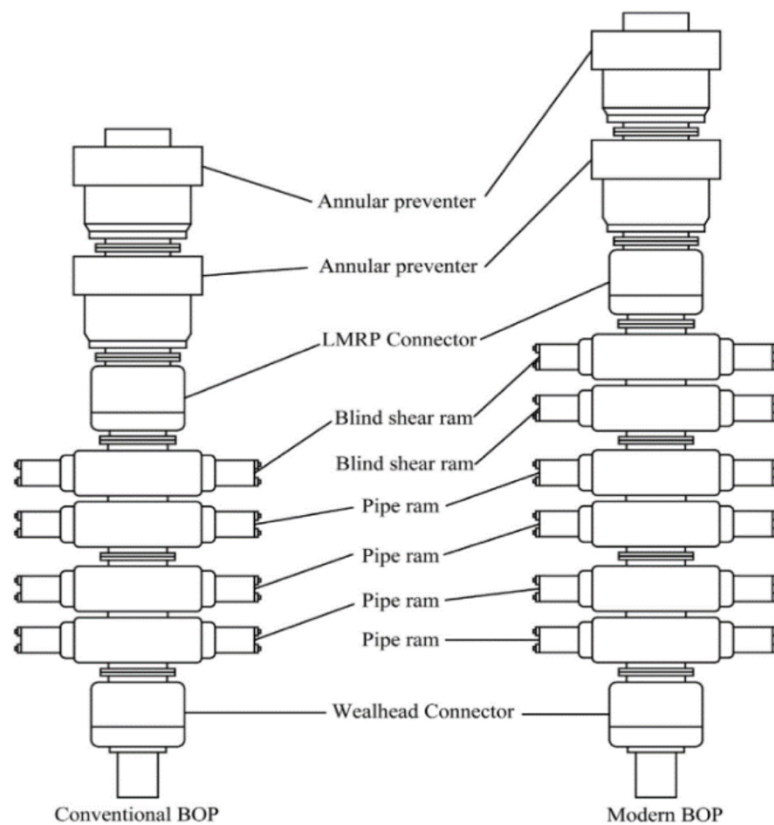


Figure 2.1 Conventional and modern BOPs (Liu *et al.*, 2015)

Based on operators' choice, BOP subsystems may differ in number, size and capacity, particularly so as exploration in deeper waters is seemingly the most prospective way forward (Hu *et al.*, 2013). Aside the failsafe function of monitoring and maintaining well integrity, the BOP system's primary functions are: (i) to confine or seal off well fluids in the well bore; (ii) to provide means of adding or withdrawing controlled volumes of fluid to and from the well bore; and (iii) to shut or 'kill' the well and seal the wellhead.

The annular or ram preventers with their associated components seal and/or shear the wellbore and its contents through hydraulic power stored and launched from accumulators. Hence, importance of the seals cannot be overemphasised. Connectors link the entire assembly to the wellhead and to the riser, which is directly hooked up to the drilling platform, whereas the choke and kill system are laden with valves, lines and hoses in order to safely transfer fluids to and from

system. A pilot control system consisting of modular pods is also embedded within the LMRP for essential control functions.

The BOP has maintained the all-important function of a drilling safety barrier since its discovery in the early 1900s. Due to its robust nature and complex assembly, little modification has been made since its entry into the oil and gas market and its acceptance as last line of defence for any drilling or workover operation. However, as oil and gas exploration moves into deeper waters and harsher environments, the potential setbacks related to reliable functioning of the BOP system and its subsystems remain a major concern for researchers, operators and other stakeholders in the industry. The BOP system failures usually result in injury/ loss of life, economic losses, environmental damage and possible damage to oil reservoir (Baugh *et al.*, 2011; Joye, 2015). According to Rausand and Engen (1983), 65% of blowouts occur through the BOP, either through the drill string or the annulus. An efficient way to avoid blowouts is to improve the design, reliability, testing and certification, and operation and maintenance (O&M) of BOP systems.

This study aims to systematically review the current state-of-the-art and present a detailed description about the recently developed methodologies for through-life management of the BOP system. The challenges associated with the BOP system design, reliability analysis, testing, deployment, as well as its operability and maintainability in the oil and gas industry are identified, analysed and discussed. For this purpose, a total of eighty-two (82) documents published since 1980's are critically reviewed and classified according to two proposed frameworks. The first framework categorises the literature based on the depth of water in which the BOP systems operate, with a subcategorization based on the Macondo disaster. The second framework categorises the literature based on the techniques applied for the reliability analysis of BOP systems, including Failure Mode and Effects Analysis (FMEA), Fault Tree Analysis (FTA), Reliability Block Diagram (RBD), Petri Net (PN), Markov modelling, Bayesian Network (BN), Monte Carlo Simulation (MCS), etc. The areas requiring further research and development will also be identified and discussed.

The rest of the paper is organized as follows. A brief description of the reviewed literature on the challenges associated with safe and reliable operation of BOPs is given in Section 2.2. The reliability analysis techniques applied for the reliability analysis of BOPs are presented in Section 2.3. Section 2.4 contains the analysis and discussions of the findings, and Section 2.5 concludes the study and provides future research directions.

2.2 The reviewed literature

This section attempts to review systematically the papers published about the challenges associated with safe and reliable operation of subsea BOPs. The review focuses on identifying drawbacks and areas of amelioration with regards to system safety and reliability as well as the techniques applied to analyse and improve the device maintainability. This implies that documents relating to other aspects such as overall functioning, historical development, general design, etc. are not inclusive. All relevant sources of literature were identified through keyword searching of databases. These sources included journal articles, conference proceedings, technical reports and governmental documents published since 1980's. Publications in languages other than English and textbooks and dissertations were excluded from the review.

Due to the varied nature and extensive scope of documentation, we propose two frameworks to classify the reviewed sources. The first framework is based on safety and reliability challenges identified in shallow water (<500), deep water (>500), or general related issues. The second framework categorises the literature based on the techniques applied for the reliability analysis of BOP systems. The classification based on water depth indicates that the research methods and findings in the document are specifically within the said boundaries. The classification 'general' will indicate any other research with no such specific boundaries but related and within the scope of analysis. Within each category, sub-divisions are identified relating literature prior to or after the Macondo disaster in the Gulf of Mexico (GoM). Investigations and research into this event has sparked a rapid evolution in safety, risk and reliability awareness of BOPs and the oil and gas industry in general.

2.2.1 Deep and shallow waters

Despite the outlined importance of the BOP, technological advancement in the petroleum industry in general has actually been a forced issue, mainly in response to business needs (Pettingill and Weimer, 2002). Drilling success rates in conventional deep water (>500 m) seemed to have peaked recently (Latham, 2002) and advances in ultra-deep (UD) zones (>1500 m) are increasingly economically feasible. Worth noting is the fact that approximately 58 billion barrel of oil equivalent (BBOE) have been discovered in deep waters, with more than half the amount found after 1995 (Pettingill and Weimer, 2002). Drilling and exploration have taken a massive leap into deep and UD waters. This affects general operation and handling of BOPs as manufacturers now face the inherent challenge of modifying the device to fit new environments, without compromising reliability.

BOPs in the 1950s were simple 1100, 3000 psi rated devices, working for a few days in depths of about 1500 ft (500m). Nowadays, newly discovered deep and UD oil fields require up to 20,000 psi rated 18 3/4" BOPs (Whitby and Kotrla, 2010), capable of lasting for the life of the well. Size notwithstanding, unexplored terrain in new water depths present unique challenges and peculiar difficulties (Rocha *et al.*, 2003). UD waters are characterized by high pressure, high temperature (HPHT) zones, gas pockets, and increasing amount of hydrogen sulphide (H₂S) with associated reliability problems such as infant mortality, depth/pressure sensitivity, environmental corrosion/erosion, saltwater ingress and design performance failures (Duell *et al.*, 2001). According to Shaughnessy *et al.* (2007), the problems associated with the increase in water depth include: weather problems, mechanical failures of subsea equipment, wellbore instability, formation and cementing issues and specifically, BOP challenges. Blowout control in these new environments has not been mastered and is often handled reactively. These issues have shaped recent BOP research as greater reliability and availability are more than ever, highly desirable. Operators and other industry partners seek to cut down the inevitable costs associated with deeper water operations without compromising the reliability of the device.

2.2.2 Pre and post Macondo disaster

The Macondo disaster that left the GOM coast flooded with more than four (4) million barrels of oil and the loss of 11 lives (Foley, 2010) resulted in a re-examination of the 'safe' perception of the oil/gas industry and one of its principal safety equipment, the BOP, in particular (Finneran *et al.*, 2013). Investigations after the disaster revealed several pitfalls within the device, which could have simply been overlooked or minimised prior to the April 2010 event. This has since led to rapid evolution of both prescriptive and performance-based regulations and safety management system requirements governing the BOP and the industry at large. A brief summary of the BOP challenges in deep waters, shallow waters and general is provided in Table 2.1, Table 2.2 and Table 2.3 respectively.

Table 2.1 Classification of BOP Challenges (deep-water related)

Category	Era	Reference	Principal Focus
		Duell <i>et al.</i> , (2001)	Identification of BP's deepwater developmental challenges and mitigation strategies
Deep water related	Pre-Macondo	Jarvis (1984)	Discussion and description of reliable acoustic control system for deepwater subsea blowout preventers (SSBOPs).
		Quilici <i>et al.</i> , (1998)	Use of qualitative risk assessment (QRA) to prioritize areas of greater reliability concern
		Holand (1999)	Evaluating failure statistics and testing time consumption for 83 GOM wells in 400-2000m water depths
		Montgomery (1995)	Positive effects of inspection and testing for high-pressure high-temperature (HPHT) BOPs
		Holand (2001)	Evaluation of downtime caused by BOP failures and testing
		Holand and Skalle (2001)	DW BOP reliability and failure rate evaluation. BOP failure calculations based on drilling cycle
		Jorge <i>et al.</i> , (2001)	Reliability analysis across different activity phases and operating conditions for subsystems

		Shanks <i>et al.</i> , (2003)	BOP control system reliability relative to maintenance goals
		Taklo <i>et al.</i> , (2004)	Risk management of surface blowout preventers (SBOPs) in DW and comparison with SSBOPs
		Childers <i>et al.</i> , (2004)	New hybrid electro-hydraulic control system development for DW BOP applications
		Amani <i>et al.</i> , (2006)	Limitations in accumulator design
		Jorge (2005)	Comparing risks of different configurations on DP rigs
		Khandoker <i>et al.</i> (2008)(Khandoker, Landthrip, & Huff, 2008)	Design challenges and solutions for BOPs (ram preventer in particular)
		Tarr <i>et al.</i> (2009)	Experience with SBOP and its advantages
		Chapman and Brown (2009)	Automatic monitoring of BOP state to improve maintenance
	Post-Macondo	Finneran <i>et al.</i> , (2013)	Forensic investigation of the Macondo BOP
		Holand and Awan (2012)	Detailed DW SSBOP reliability evaluation and kick data for 259 wells in the GOM OCS
		Whooley <i>et al.</i> , (2011)	Risk assessment options for operating different BOP configurations (SSBOP and SBOP with SID)
		Bhandari <i>et al.</i> , (2015)	Risk analysis of drilling in DW with considerations to leakage in ram preventer in particular
		Mutlu <i>et al.</i> , (2018a)	Condition and performance monitoring of a pressure regulator employed on deepwater BOPs
		Yamamoto and Marooka (2019)	Feedback control system for the automatic approach of the BOP to the wellhead

Table 2.2 Classification of BOP Challenges (Shallow water related)

Category	Era	Reference	Principal Focus
	Pre-Macondo	Rausand and Engen (1983)	Identifying most failure prone components and reasons for rig

Shallow water related			downtime. (control system most prone)
		Holand and Molnes (1986)	Use of qualitative risk assessment (QRA) to prioritize areas of greater reliability concern
		Holand and Rausand (1987)	Evaluating failure statistics and testing time consumption for 83 GOM wells in 400-2000m water depths
		Holand (1991)	Positive effects of inspection and testing for high-pressure high-temperature (HPHT) BOPs
		Sattler and Gallander (2010)	Evaluation of downtime caused by BOP failures and testing
	Post-Macondo	-	-

Table 2.3 Classification of BOP challenges (General)

Category	Era	Reference	Principal focus
General	Pre-Macondo	Kostriba (1980)	Discussing difficulties with seals
		Holand (1985)	Reliability of SSBOPs
		Holand (1987)	Reliability of SSBOPs from 1982-1987
		Varcoe (1991)	Investigating accumulator size and its relation to shearing
		McWhorter (1993)	Design considerations and product performance of ram preventer seals
		Montgomery (1993)	Reliability of SBOPs in comparison to SSBOPs
		Fowler and Roche (1993)	Overall system reliability based on FMEA and FTA
		Holand (2011)	FTA of subsea BOP with and without backup systems
		Holand (1997)	Using FTA in BOP reliability analysis
		Holand and Skalle (2001)	Proposal of alternative BOP configuration to improve availability
		Al-Shammari and	Discussion on how specific drilling environment affect BOP stack arrangements,

		Nordquist (2003)	kill/choke line requirements, replacement part criteria, elastomer application limits, and the use of variable bore rams and shear blind rams
		West Engineering Services (2003)	Review design capabilities of BOP secondary interventions systems
		West Engineering Services (2004)	Investigating shear ram capabilities particularly during erratic conditions
		Song <i>et al.</i> , (2006)	Improving control system response time
	Post-Macondo	Cai <i>et al.</i> , (2012a)	Control system reliability subjected to multiple error shocks
		Shanks <i>et al.</i> , (2012)	Ameliorating shearing capabilities of SSBOP
		Cai <i>et al.</i> , (2012b)	Reliability of SSBOP control system
		Bureau of Safety and Environmental Enforcement (BSEE), (2013a)	BOP thorough RAM Analysis
		Bureau of Safety and Environmental Enforcement (BSEE), (2013b)	Using FMECA to evaluate system and subsystem causes and effects of loss of functionality
		Sattler (2013)	Post–Macondo process and procedural changes
		Cai <i>et al.</i> , (2013a)	Reliability based on repair and maintenance strategies
		Liu and Liu (2019)	Using Bayesian networks from GO models for reliability analysis of BOP control system
		Liu <i>et al.</i> , (2013)	Evaluating the effects of diagnostic and repair rates on the performance (RAMS) of SSBOP using Stochastic Petri Nets
		Cai <i>et al.</i> , (2013b)	Quantitative risk analysis of overall SSBOP operations
		Zengkai <i>et al.</i> , (2013a)	Employing Petri nets for reliability and availability analysis of annular preventer

		Nae <i>et al.</i> , (2014)	New approach for monitoring assembly, disassembly and maintenance operations on BOPs
		Tulimilli <i>et al.</i> , (2014)	Design study of shear rams based on simulation and sensitivity analysis
		Abimbola <i>et al.</i> , (2014)	Dynamic safety assessment approach based on Bow-tie analysis for drilling equipment is presented
		Kim <i>et al.</i> , (2014)	Markov modelling of reliability considering common-cause failures and redundancy
		Liu <i>et al.</i> , (2015a)	Availability and reliability of SSBOP components using Petri nets, considering effects of failure rates and repair time
		Lukin and de Souza (2015)	Risk analysis of annular preventer using FTA
		Okonji (2015)	FMECA with MCDM for reliability analysis
		Cai <i>et al.</i> , (2015)	Reliability evaluation of subsea pipe ram preventer using dynamic Bayesian networks (DBN)
		Liu <i>et al.</i> , (2015b)	Fault diagnosis of hydraulic control system using DBN
		Strand and Lundteigen (2015)	Using Markov modelling to evaluate aspects of safety performance and maintenance optimisation
		Liu <i>et al.</i> , (2015c)	Reliability using DBN and focus on common-cause failures
		Khakzad <i>et al.</i> , (2015)	Usage of precursor data and approximate reasoning to evaluate reliability
		Han <i>et al.</i> , (2015)	Studying damage and failure of shear ram and its effects on the shearing process
		Chung <i>et al.</i> , (2016)	Evaluation of SSBOP safety integrity levels
		Zou <i>et al.</i> , (2016)	BOP system and subsystem reliability and testing
		Nouri <i>et al.</i> , (2016)	Reliability and availability improvements using expanded FMEA
		Pui <i>et al.</i> , (2017)	Novel risk-based methodology for maintenance scheduling
		Zhang <i>et al.</i> , (2018)	Reliability analysis of annular BOP using FTA and fuzzy relation analysis theory

		Brandão Martins <i>et al.</i> , (2018)	PHM and CBM concepts towards BOP reliability
		Mutlu <i>et al.</i> , (2018b)	Performance analysis of subsea BOP hydraulic seals
		Liu <i>et al.</i> , (2018)	Risk analysis of BOP by mapping GO model into equivalent BNs
		Mutlu <i>et al.</i> , (2018c)	Real-time condition and performance monitoring of BOP using adaptive physics-based models
		Wu <i>et al.</i> , (2018)	Availability analysis of blind shear ram preventer using Markov model
		Mutlu <i>et al.</i> , (2017)	Qualitative FTA for availability of BOP with respect to different requirements
		Shafiee <i>et al.</i> , (2019)	Risk analysis of BOPs using hybrid of FTA and FMEA
		Liu and Liu (2019)	Reliability analysis of BOPs using BNs constructed from GO models
		Elusakin <i>et al.</i> , (2019)	Implementing condition-based maintenance to improve reliability of subsea BOP
		Wassar <i>et al.</i> , (2019)	Health monitoring of annular blowout preventers
		Elusakin and Shafiee (2020)	Reliability analysis of BOPs with condition-based maintenance using stochastic Petri nets
		Yin <i>et al.</i> , (2021)	Quantitative risk analysis of well blowouts using BNs

With regard to the oil and gas industry, regulatory changes started with the dissolution of the Mineral Management Service (MMS) – which had been in charge of the safety and security of operations on the outer continental shelf (OCS) – and its replacement with the Bureau of Ocean Energy Management (BOEM) and Bureau of Safety and Environment Enforcement (BSEE) (Snow, 2012). Changes were also made to the drilling safety rules, worst-case blowout response and well-containment measures (SCOR Global, 2014). The Macondo incident also had a profound impact on theoretical research. In the wake of the accident, the amount of research performed focusing on the reliability of offshore drilling assets and more specifically, BOP reliability, increased markedly as the BOP increased in relative significance. Going by the sheer volume, the amount of research performed on BOP reliability in the ten years following the Macondo

incident greatly exceeds the amount of research performed in the three decades prior.

2.3 BOP reliability analysis techniques

This section reviews the results of the classification framework based on the techniques adopted for reliability analysis of BOP systems. Only literature with subject matter relating to BOP reliability analysis have been included in this classification. The purpose of this framework is to better categorize existing research and ease further studies in BOP reliability analysis.

In response to recent events in the industry, a lot of attention has been shown to the reliability of BOP systems. However, research on the topic is still lacking in some regard (Liu *et al.*, 2015c). The reliability assessment of subsea BOP systems has come a long way since Holand and Rausand (1987) used a combination of drilling, BOP test, well and equipment failure reports and applied Fault Tree Analysis (FTA) as a means of reliability assessment. Some years later, Fowler and Roche, (1993) applied FTA and Failure Mode and Effects Analysis (FMEA) to assess the reliability of a subsea BOP and a hydraulic control system. Reliability Block Diagrams (RBDs) were also used by Zou *et al.*, (2016) to model the reliability performance of subsea BOPs and then the results were compared against design requirements. Advanced reliability analysis techniques which provide more robust solutions have also been applied in recent years, however, gaps still exist with regards to incorporation of maintenance strategies and dynamic operating condition of the BOPs.

The reliability analysis techniques discussed within this review focus on the application to subsea BOPs and their components. The following subsections give brief summaries on each technique.

2.3.1 Failure mode and effect analysis

The application of FMEA as a technique to assess system reliability dates back for five decades and its use and effectiveness in a myriad of industries is well documented. The FMEA process begins with a qualitative analysis of the system in question and its functions followed by a quantitative analysis which explores

each component, identifies their failure modes and determines the effects of those failure modes on the overall system.

A risk priority number (RPN) which serves as a means to prioritise and rank the identified risks is developed. It considers three factors: severity of impact (S), likelihood of occurrence (O) and likelihood of detection (D) (Kolios *et al.*, 2017). Although it has been criticized on multiple occasions over time on account of the RPN (Dinmohammadi and Shafiee, 2014; Shafiee and Dinmohammadi, 2014), it possesses quite a number of advantages which help justify its use as a reliability assessment technique. The FMEA technique can be used to identify failure modes and evaluate risks early in the design process, it ensures that risks are comprehensively identified and categorised, and it helps the analyst determine the system's functional vulnerabilities (David *et al.*, 2011). The FMEA technique has been applied a number of times towards analysis of BOP reliability in literature. The technique was applied in (Bureau of Safety and Environmental Enforcement, BSEE (2013b) towards three BOP reliability analyses performed on specific BOP components. Shafiee *et al.*, (2019) also discussed its application in conjunction with FTA in order to perform risk analysis on a subsea BOP. When a criticality is involved, the analysis is referred to as Failure Mode, Effects and Criticality Analysis (FMECA).

2.3.2 Fault tree analysis (FTA)

The fundamental theory of FTA is the conversion of a system into an organized logic structure (Lee *et al.*, 1985). Over time, its definition has evolved to being a diagram which depicts the relationships between a possible critical event in the system and its causes (Rausand and Hoyland, 2004). In terms of system maintenance, FTA allows operators identify and then qualify the initiating failure causes that will help set the stage for developing a maintenance program fit to maintain system reliability at the required level (García Marquez *et al.*, 2012). There are two types of nodes which make up a fault tree, namely: the event nodes and gate node. Events can be either *basic* (meaning they cannot be deconstructed into smaller events) or *intermediate* (meaning they are represented as a combination of basic events and other intermediate events)

(Kang *et al.*, 2019). The types of gates include the AND gate (which represents the combination of all inputs to produce the output event) and the OR gate (which represents the existence of the output provided at least one of the input events exists) (Lee *et al.*, 1985). Performing FTA consists of the following steps (Lin *et al.*, 2014):

- System and boundary definition,
- Fault tree construction,
- Minimal cut set definition,
- Qualitative analysis,
- Quantitative analysis.

The FTA technique has been applied for the analysis of BOP reliability in a number of studies. Holand and Rausand, (1987) used it in conjunction with failure reports as a means of assessing the reliability of subsea BOPs. Mutlu *et al.*, (2017) performed a qualitative FTA to assess the reliability of a BOP control system. In another study, Zhang *et al.*, (2018) discussed its application in combination with fuzzy analysis theory to determine the reasons for failure of an annular BOP.

2.3.3 Markov modelling (MM)

The Markov method is a modelling technique applied to analyse the reliability of fault tolerant systems (Boyd, 1998). It depicts the system to be analysed using state circles and transition arcs which form a Markov transition diagram. The Markov method is known for being flexible and has been noted in several literature as being uniquely suitable for reliability assessment of redundant systems such as BOP (Cai *et al.*, 2012c). It also is a very suitable technique to solve dynamic problems which conventional reliability analysis techniques such as FTA and FMEA cannot deal with. The Markov chain, which is a stochastic process that possesses a Markov property, is used to model multi-state systems as well as the transitions between the states. It can be described as discrete-time or continuous-time depending on the time variable for a particular process

(Rausand and Hoyland, 2004). The Markov method does have its shortcomings. For instance, it can be quite tedious to determine transition rates due to lack of data. Also, in some complex systems, it is very possible that some states and transitions are omitted when defining both elements (Han, 2015). In literature, Kim *et al.*, (2014) applied the Markov modelling to reliability analysis of subsea BOPs by considering demand rate for its components.

2.3.4 Monte-Carlo Simulation (MCS)

Monte Carlo simulation is one of the most commonly used tools for reliability analysis of engineering systems. This is due to its independence from the complexities of the problem it is trying to solve (Li *et al.*, 2018). The main drawback associated with MCS is its inaccuracy and inefficiency in dealing with very small failure probabilities. To overcome this shortcoming, subset simulation (SS) was developed (Au *et al.*, 2007). SS is a simulation tool used for handling small failure probabilities. Using SS requires expressing the failure probability of the event in question as an amalgamation of chosen smaller probabilities (Au and Beck, 2001). SS has been applied to different engineering systems such as reliability of subsea pipelines (Li *et al.*, 2018), dynamic stiffness of large offshore wind turbines (Le and Andrews, 2016), and so on.

2.3.5 Petri net (PN)

The PN concept, which was developed by Dr Carl Petri as part of his PhD dissertation, is a reliability method applied to modelling and assessment of non-deterministic, parallel systems (Liu *et al.*, 2015a). As an extremely versatile technique, it can be used to evaluate redundant systems, manufacturing systems, and safety-critical elements, among others (Liu *et al.*, 2013; Talebberrouane *et al.*, 2016; Shah *et al.*, 2017). The technique can be used as a graphical tool – for aiding visual communication, and as a mathematical tool – for developing mathematical models which govern the behaviour of systems (Sadou and Demmou, 2009). There are four main modelling elements which make up the PN. These include: places, arcs, transitions and tokens. Places are denoted by circles, transitions by rectangles, tokens by solid circles which are located inside places and arcs connect places with transitions. There are multiple variations to

the PN technique such as the coloured petri net (CPN), the stochastic petri net (SPN) and the deterministic and stochastic petri net (DSPN). The SPN is very suitable for complex dynamic systems such as the BOP due to the fact that it explicitly introduces the time parameter (Zengkai *et al.*, 2013b). In a recent study, Elusakin and Shafiee, (2020) applied the SPN technique to analyse the reliability of subsea BOPs with different failure modes subject to condition-based maintenance (CBM).

2.3.6 Bayesian Network (BN)

According to Langseth and Portinale (Langseth and Portinale, 2007), BN is a compact representation of a multi-variate statistical distribution function. The BN technique has recently come into prominence as being a more robust and viable alternative to the conventional reliability assessment techniques such as FTA and FMEA (Liu *et al.*, 2015c). This is mainly due to the fact that BN can perform predictive as well as diagnostic analyses (Cai *et al.*, 2012b). For reliability assessment, BN models are developed by converting and building on the conventional reliability models. A BN model is made up of qualitative and quantitative sections. The qualitative section is a directed acyclic graph (DAG) containing nodes and arcs which denote the system variables and their dependencies respectively. The quantitative section highlights the connections between each node and its parents through a conditional probabilistic table (Cai *et al.*, 2013a). Variations to the BN technique can be applied to evaluate system reliability based on the type of system and operating circumstances. For example, dynamic Bayesian networks (DBNs) is applied when temporal features are involved in reliability analysis. Object-oriented Bayesian networks (OOBNs) are appropriate for analysing the reliability of sizeable, complex structures. Dynamic object-oriented Bayesian networks (DOOBNs) are used to analyse degrading components as well as repetitive systems (Yuan *et al.*, 2018). The BN technique has been applied to BOP system reliability analysis in a number of studies. Readers can refer to Cai *et al.*, (2013b), Cai *et al.*, (2015), Liu *et al.*, (2015b), Wu *et al.*, (2018) and Liu and Liu, (2019) for further reading.

2.3.7 Reliability Block Diagram (RBD)

RBD is a graphical framework in the form of block diagrams which represents how functioning components of a system form logical connections to complete a specific system function. It is suited mainly to non-repairable components and scenarios where the order in which failures occur is not important (Rausand and Hoyland, 2004). RBDs have three main structural configurations: series, parallel and a mixture of the two. A series configuration represents all the blocks (or components) being required to work for the system to function. A parallel configuration represents only one component being required for the system to successfully function. A prime example of this is component redundancy. A mixture configuration is used to represent more complex models. An example of this being if a series system gets duplicated or made redundant. RBDs depicting system reliability are more often represented as a mixture of series and parallel structure configurations (BSI Group, 2016). In literature, the RBD technique has been used as part of reliability analysis to ascertain the impact of testing, inspection and maintenance actions on the BOP availability (Jia *et al.*, 2019).

Table 2.4 shows the distribution of published literature among the different reliability analysis techniques discussed.

Table 2.4 Distribution of the literature by BOP reliability analysis techniques

Reference	FMECA	FMEA	FTA	MM	MCS	RBD	PN	BN
Holand (1999)			✓					
Holand and Skalle (2001)			✓					
Holand and Awan (2012)	✓							
Bhandari <i>et al.</i> , (2015)								✓
Holand and Rausand (1987)			✓					
Fowler and Roche (1993)		✓	✓					
Cai <i>et al.</i> , (2012a)				✓				

Reference	FMECA	FMEA	FTA	MM	MCS	RBD	PN	BN
Cai <i>et al.</i> , (2012b)								✓
Bureau of Safety and Environmental Enforcement (BSEE), (2013a)						✓		
Bureau of Safety and Environmental Enforcement (BSEE), (2013b)	✓							
Sattler (2013)	✓							
Cai <i>et al.</i> , (2013a)								✓
Liu and Liu (2019)								✓
Liu <i>et al.</i> , (2013)							✓	
Cai <i>et al.</i> , (2013b)								✓
Zenkai <i>et al.</i> , (2014)							✓	
Abimbola <i>et al.</i> , (2014)			✓					
Kim <i>et al.</i> , (2014)				✓				
Liu <i>et al.</i> , (2015a)							✓	
Lukin and de Souza (2015)			✓					
Cai <i>et al.</i> , (2015)								✓
Liu <i>et al.</i> , (2015b)								✓
Liu <i>et al.</i> , (2015c)								✓
Chung <i>et al.</i> , (2016)						✓		
Zou <i>et al.</i> , (2016)	✓	✓						

Reference	FMECA	FMEA	FTA	MM	MCS	RBD	PN	BN
Nouri <i>et al.</i> , (2016)		✓						
Shafiee <i>et al.</i> , (2019)		✓	✓					
Liu <i>et al.</i> , (2018)								✓
Wu <i>et al.</i> , (2018)				✓				
Mutlu <i>et al.</i> , (2017)			✓					
Lin <i>et al.</i> , (2014)				✓				
Langseth and Portinale (2007)			✓					
Yuan <i>et al.</i> , (2018)						✓		
BSI Group (2016)			✓					
Jia <i>et al.</i> , (2019)			✓					
Liu and Liu (2019)								✓
Elusakin and Shafiee (2020)							✓	
Yin <i>et al.</i> , (2021)								✓

From table 2.4, it is evident that the BN technique is the most used for reliability analysis of subsea BOPs and the MCS technique is the least. The lack of use of the MCS technique is emblematic of one of its main disadvantages which is that it is computationally expensive.

2.4 Observations and findings

2.4.1 Observations

From the documents reviewed, prominent challenges associated with the BOP can be grouped into three principal categories: design, deployment, and operation. Design challenges are mainly related to sealing, shearing, and accumulator issues; deployment challenges are associated with recent developments in BOP technology; and operational challenges are related with the testing, inspection and maintenance, and extreme operating or environmental

conditions. These three categories are addressed in more detail in the following sections:

2.4.1.1 Design Challenges

Sealing elements

Due to their soft, nearly incompressible elastic properties, complex elastomeric polymers which are the main components of seals are used to support deformation and compression in different preventer types. According to API SPEC 16A, (2017), these polymers must be capable of sealing and preventing leaks. However, leaks are common and generally associated with inappropriate elastomer selection (Al-Hiddabi *et al.*, 2015; Sugama *et al.*, 2015). High temperature nitrile elements in packer seals have a limited useable temperature range (Lin *et al.*, 1992) and are subject to extrusion and abrasion. Though largely elastic, they undergo stress relaxation, creep, damping and increased stiffness with frequency of loading, which is likely to worsen in unpredictable environments.

Surrounding drilling conditions usually affect seals in two major ways: chemical degradation under high temperatures or stiffness/brittleness and swelling due to fluid absorption after prolonged exposure. Since abrasion and extrusion cannot be totally avoided in specific parts like elastomeric ram packers, degradation rates are simply reduced to achieve the desired sealing property (McWhorter, 1993). Material selection for specific applications, fluid compatibility and operating conditions on a holistic platform is necessary for increased reliability in deep and UD waters.

Shearing Capabilities

Blind and casing shear ram preventers are fitted with blades, to cut through different tubing types, and seal off a well. Failure to shear is not very common (Shaughnessy *et al.*, 2007). However, as drilling advances into UD waters, drill pipe properties such as material strength, toughness and ductility are continuously improved to reduce drill pipe failures and increase their life span, which result in increased shearing force requirements. Studies attribute failure-to-shear to material composition (Jellison *et al.*, 2008) and other increasing

exogenous parameters include drilling fluid density and shut-in pressure. Inability to cut through drill collars, drill bits, tool joints, connectors and other drill pipe attachments are not uncommon. According to Rassenfoss, (2012), the Bureau of Safety and Environmental Enforcement (BSEE), after several months of investigation, recognized the importance of the BOP being 'shear certain', a requirement which may well become part of the developing industry regulations. Though current BOP designs are ambiguous, the industry is pre-disposed to achieve this goal. Laser application, stronger bladders, use of explosives, greater hydraulic cutting pressure, are all technologies under study. New shear ram designs are already available in the BOP markets (Medina *et al.*, 2011). Some companies like Shell and BP have started the implementation of two blind shear rams in one stack arrangement (Rassenfoss, 2012) as a means to ensure shearing/sealing, hence improving reliability though it is a more costly option due to mobility and weight challenges. The manufacturing of strong yet shear-able drill collars (with thinner skins and lead centres) is another feasible solution (Baugh *et al.*, 2011).

Accumulator design and capacity

One way to tackle the vagaries of UD environments is to modify the distance from surface and number of accumulator bottles. The further accumulator bottles are located, the lower the useable fluid volume per accumulator bottle (Amani *et al.*, 2006), as actuation pressure reduces with distance travelled. When accumulator bottles are used, communication must be established with control pods via control lines. Reaction time for different line diameters varies and operates by a power law relationship. A small diameter control line at 400ft (122m) may react anywhere within 1 and 10s in depths of 3000ft (914m) (Watson *et al.*, 2003), increasing command-to-completion time. Many techniques have been developed to solve this problem when the BOP is connected to the riser.

In emergency situations, the act of shearing or dropping the drill string may become mandatory if rig control is lost and a functional BOP with sufficient accumulator volume should be able to complete this task. In deep and UD water depths, the accumulator bottles could become prohibitory due to increased

expense and floater capability to handle such large LMRPs. At these depths however, charging and replenishing accumulator canisters can only be done by remotely operated vehicles (ROV) intervention, an area of continual questionable reliability (Mason *et al.*, 2005). As the Emergency Disconnect System (EDS), Deadman switch and blind shear rams depend solely on the proper functioning of hydraulics, their independence from main controls in the event of blackouts and loss of power are vital.

2.4.1.2 Deployment challenges

Commissioning and decommissioning of BOPs are fairly simple with on-board cranes and hoisting systems in shallow waters. In deep-water locations, the project's cost and schedule contribute immensely to the overall installation activity. A winch with 20m/min speed for deployment at 2500m water depth is likely to span an entire day for installation and recovery process (Rowe *et al.*, 2001) and even more so in adverse met-ocean conditions. All the more, recent inevitable redundancy and increased safety measures have created a weight and size footprint in subsea hardware. Modern BOPs are much larger and heavier than conventional ones. They weigh about 450tons and have 60ft (18m) of height (Tulimilli *et al.*, 2014). Typical deep-water fields also comprise of several blocks and reservoirs in extensive areas, making installation and maintenance costly and time-consuming. Three factors are of primary concern with regards to subsea deployment: handling technology, load control and positioning, and met-ocean and weather effects.

The third and fourth generations of BOP systems have become popular over the past 20 years. The new systems employ casing risers in place of flexible tube risers and a Subsea Isolation Device (SID), placed on the seabed (Mason *et al.*, 2005). A Subsea Deployment System (SDS) has also been applied, making use of a fully floodable solid buoyancy hull with chains attached to float equipment being deployed in water (Cermelli *et al.*, 2003). Though it is said to save cost and time with low risks for transporting heavy equipment in deep water and harsh environments, weight limitations make it difficult to operate beyond a limited water

depth. Positioning issues such as dynamic responses, positioning reference issues, soil conditions etc. are also worth considering.

2.4.1.3 Operational challenges

In spite of having high availability levels (Holand, 1991; Cai *et al.*, 2012c), BOP failures are continually reported, and the device does not seem to work properly when required (Grace, 2003). In the Macondo disaster, though the device had been tested some days earlier and deemed fit for purpose, it failed in a similar sequence to most oil and gas disasters (Vinnem and Røed, 2014). Subsea operating conditions have now gone beyond those specified in 30 CFR 250.517 (2012), API 17N (2017), API RP 53 (1997) and API SPEC 16A (2017). Standard development and compliance activities lag behind the increasing pace of technology development (Carter *et al.*, 2014). The rewrite of API RP 53 (1997), which is coded as API STD 53 (2018) remains a major regulatory milestone and places additional strength to the articulated requirements (Sattler, 2013). The industry has now realised that a high level of reliability and integrity is a key requirement for the operation of subsea systems (Strutt *et al.*, 2012).

Environmental conditions

New operating environment remains a fundamental challenge, flooded with high gas-oil ratios, HPHT regions, elevated tides and wave currents, difficult formations and even lack of experienced personnel (Han, 2015). Since 1992, more than 1500 wells have been drilled in water depths exceeding 500m (1500 feet) and approximately 320 wells were drilled in water depths greater than 1500m (5000ft). Safety and environmental concerns are not limited to deep-water but stakes are relatively higher in deep waters compared to shallow waters since costs of mishap are proportionately higher.

BOPs were used on conventional land wells till hydrocarbon deposits were discovered on the ocean floors. These devices translated their safety and control function to land rigs which were mounted on barges several decades ago. This became common practice for jack-up rigs as drilling moved to shallow waters and extended depth capabilities to about 650 feet. Then, semi-submersible rigs and

drillship evolved, moving water depths to 1500 feet and the BOP to the seabed. This move enabled the use of low pressure and less expensive risers to connect and transport the drill fluid back to the rig. This flexibility helped industries develop capabilities of drilling rigs in locations with depth of 3000m (10,000 ft) (Kotrla *et al.*, 2002). However, the initial advantage of cost savings has phased out over the years as greater depths have different requirements.

Testing, inspection and maintenance

Minimal exogenous risk analysis is carried out during the operational life of a BOP. The awareness of changing environmental conditions will certainly alter the outlook on testing, inspection and maintenance specified by API RP 53 (1997) and BSEE 30 CFR 250.517 (2012). The claim that continuous usage and testing of the BOP will cause wear, therefore sometimes accounting for failure (Holand, 1991), is not uncommon and is possibly the reason for its usage only as a 'last' resort during incidents. Subjecting BOPs to high pressure testing may cause wear, vibration, leaks and fracture which, if not properly maintained and monitored, can result in a disaster. However, tests are essential to ascertain proper functioning and maintenance procedures. Financial implications of about 5% of drilling time notwithstanding (Holand, 2001), tests cannot be overlooked. There remains a possibility that due to above mentioned factors and other human limitations, test procedures are generally neglected by the drilling crew and/or regulatory bodies.

Ram locks are a vital part of ram block in a BOP system and a classic example of a component which is not usually tested. API SPEC 16A (2017) does not require testing of these locks when manufactured. API qualification pressure and sealing tests are carried out on new BOPs like other pressure containment equipment and rated solely on bore size and design. No reference to external loads or water depths are provided (Khandoker *et al.*, 2008). According to these specifications, a good BOP test means no visible leaks. Local bearing stress and fatigue calculations are also not considered. Many such leaks are not detected due to high pressures employed in today's large BOPs. Visual inspections are necessary to detect leaks and should be carried out by personnel who know

where to look within the system. Progressing from a repair-on-failure philosophy, maintenance is an obvious tool for improving reliability. Eliminating data acquisition difficulties in the oil and gas industry will make Reliability Centred Maintenance (RCM) more applicable. Maintenance logbooks may become necessary for the BOP system as well as its components in the oil and gas industry. The amount of time between BOP repairs may need to be regularly recorded. Incorrect, insufficient, inefficient and untimely maintenance may be the trigger to barrier failure (Okoh and Haugen, 2013).

Although commonalities such as risk-based inspection (RBI) and robotic inspection technologies exist, the use of non-destructive testing (NDT) techniques will enhance the performance of BOPs in deeper waters (Duell *et al.*, 2001, McKay *et al.*, 2012). Techniques such as vibration analysis, infrared thermography, acoustic emission and ultrasound analysis can be adapted for BOP inspection (Papatzimos *et al.*, 2018). Although vibrational analysis is costly and invasive, infrared thermography, acoustic emissions and ultrasound analysis are non-intrusive and can provide data on a more real-time basis. However, the infrared and acoustic based techniques are more susceptible to error and the ultrasound analysis requires more thorough understanding. These techniques, among others already play a role in the maintenance of offshore drilling assets and are poised to be applied to subsea BOP maintenance in the future (Elusakin *et al.*, 2019).

In order to test the basic functionality of the BOP control system, its software is subjected to extensive regression testing which leads to unwanted errors. To overcome this, the hardware-in-the-loop (HIL) testing methodology, which is a staple in the aerospace industry can be applied (Silva *et al.*, 2019). HIL testing involves the integration of actual working equipment into a simulated environment and this can be used to test the BOP control system software without adding unnecessary new functions or modifications (Kårvand *et al.*, 2017).

Reliability

With reliability being a foundational attribute for the safe operation of BOPs, ensuring and maintaining high system reliability constitutes a fundamental

challenge. Reliability analysis is therefore performed to address the protective barriers of the BOP components. The BOP, being a modern drilling system, is mainly constituted of hardware, software, human and organisational elements. The combination of these factors coupled with the focus on failures relating to hardware and software raises the relative significance of errors which occur in human and organisational elements. In addition, complex operational tasks such as maintenance must not just be performed for its own sake, but to ensure consistency between BOP reliability characteristics and production as well as regulatory directives (Edgar and Manz, 2017).

2.4.2 Review findings

Critical analysis of the literature reveals the current state-of-the-art in subsea BOP operational safety, any progress achieved, and exposes areas requiring further regulatory, design and research ameliorations. More so, it is clear that there has been increasing attention, particularly after 2010, on the safety of subsea BOPs, emphasising the wake-up call by the Macondo disaster.

Pre-Macondo concerns related to the BOP are limited to overall reliability. External leakage, failure to seal, and lower reliability of surface preventers (McWhorter, 1993) account for approximately 53% of the reviewed documents. Post-Macondo however has witnessed a slight shift in focus. The years following the disaster has witnessed major regulatory changes, several joint industry projects and even a complete re-write of the API RP 53 (1997), now API STD 53 (2018). Researchers have intensified concerns with regards to real-time monitoring (Zio, 2009; Huse and Alme, 2013b), risk monitoring (Asten, 2013) and modelling (He *et al.*, 2014).

Continual refining of design elements such as shearing blades and sealing elements are paramount in UD drilling. Active component redundancy and even entire system replacement spares are gaining increasing interest in the industry. The hydraulic control system, ram preventers, and hydraulic connectors fail more frequently and require unabated design amelioration as understanding of the new oceanographic conditions is gained. More so, aspects discussed herein are largely analogous and intermittently affect each other. Design improvements

such as active redundancy may create a weight/size footprint, which in turn affects deployment. This implies BOP challenges, though diverse and far reaching, should be treated in a consolidated fashion.

About twenty-five percent of the reviewed literature focused on deep-water related issues, whilst little attention has been paid to shallow water issues specifically post-Macondo. It is however important to note that the documents classified as 'general' specific reference were not made to either deep or shallow water but they may still be applicable in either case. Several factors may be responsible for this but principally, by 2010, focus had greatly shifted to deep and UD waters. Aside from individual researchers, significant efforts were made by bodies such as the Foundation for Scientific and Industrial Research at the Norwegian Institute of Technology (SINTEF), the U.S. Mineral Management Services (MMS) which is now Bureau of Ocean Energy Management (BOEM) and Bureau of Safety and Environmental Enforcement (BSEE).

Other findings in terms of failure prone subsystems, common-cause failure and component redundancy as well as conventional and advanced reliability analysis techniques for subsea BOP systems are also discussed in followings.

Failure prone subsystems

Studies reveal that some BOP subsystems fail more frequently and impair the overall reliability of the device. According to Holand (1991), a study of 183/4 inch, 10000–15000psi rated subsea BOPs between the years 1978 and 1989 revealed that annular preventers, choke/kill lines and the hydraulic control system contributed approximately 79% of rig downtime. Choke/kill lines and the hydraulic control system experienced majority of failures within the study period. Other contemporary studies (Abimbola *et al.*, 2014; Jia *et al.*, 2019) employing the Offshore and Onshore Reliability Data (OREDA) as data source agree in many ways with the latter. Slight variations are presented again by Holand (1997), where deep-water wells (>400m) in the Gulf of Mexico were studied and main data sources included daily drilling and BOP test reports. Ram preventers seem to fail on a similar scale to control systems and choke/kill valves. Cai *et al.*, (2012c) validated these results, proving that ram preventers, annular preventers,

LMRP connector and wellhead connectors were the main components responsible for stack failure whilst the upper annular preventer, control pods and LMRP connector require greater maintenance effort. Pareto analysis of the results showed the subsystems that require urgent design improvement. Over time, research and innovation programs have employed system and component redundancy to improve BOP reliability. Control pods, annular preventers, ram preventers, control stations and several valves are all redundantly configured for this purpose (Liu *et al.*, 2015a).

Common-cause failure and component redundancy

Common-cause failures have proven over time to have a dominant impact on accidents (Cai *et al.*, 2012b). Redundancy in BOPs was an issue in the past when unique valves and other controls operated major mechanisms within the system. To enhance the reliability characteristics of a coherent system, redundant components may be provided, using active redundancy for component redundancy or system redundancy. Nowadays, rigs equipped with spare BOPs are common (Lin *et al.*, 2014). Industry introduced backups into the BOP system but over the years, due to weight, space and other considerations, modern systems, especially control systems incorporate less redundancy. Generally, the control stations, control pods, annular preventers and ram preventers are redundantly configured. However, the entire system can be considered as a series system, since the failure of any major component category results in the failure of the entire system. A single failure in the hydraulics may cause total loss of control and such problems have been observed in the past (Skogdalen and Vinnem, 2012). Common cause failures of various existing redundant devices in the control system of the subsea BOP are known to reduce the reliability greatly (Cai *et al.*, 2012b). Attempts to activate the Deepwater Horizon shear ram as well as the EDS failed as a result of the failure of other systems, resulting in a complete failure of the BOP.

Conventional and advanced reliability analysis

Conventional reliability assessment methods have their own drawbacks. According to Bai and Bai, (2012), complex systems are difficult to model using

the RBD technique and computing the system's reliability numerically can be a time-consuming task. Both the FTA and FMEA techniques only work well for non-repairable systems and do not possess a time element, a characteristic which is extremely important when analysing subsea systems such as the BOP. In addition, the FMEA cannot differentiate a situation of common-cause failures or severe failures caused by compound failures and the FTA technique itself is not suitable for analysis of sequential events (Liu *et al.*, 2015a). Advanced reliability techniques such as Petri Net (PN), Markov Method, Bayesian Network (BN), Monte-Carlo Simulation (MCS) and their different variations have been developed and applied to assess the reliability of subsea BOPs. These advanced techniques help overcome some of the drawbacks of the conventional reliability assessment techniques (Liu *et al.*, 2017). The BN technique for example has come into prominence recently as being a more robust and viable alternative to the conventional reliability assessment techniques (Liu *et al.*, 2015c). The Markov Method technique as well as the semi-Markov method are regularly used to evaluate complex systems such as the subsea BOP due to their flexibility in representing the dynamic behaviour of the system (Lin *et al.*, 2014). The PN technique is a numerical and graphical tool used to model asynchronous, simultaneous, distributed and parallel systems (Talebberrouane *et al.*, 2016). One of its variations, Stochastic Petri Net (SPN) is very suitable for complex dynamic systems because it explicitly introduces a time parameter (Cai *et al.*, 2013a).

2.5 Conclusions

Despite the economic challenges in the current oil and gas market, the prospects of this resource remaining the world's main energy supplier are huge. Economically viable fields are still being discovered in waters of greater depths and unexplored terrain. This, however, raises questions regarding reliability, particularly that of the all-important drilling safety device, the blowout preventer (BOP). This chapter aimed to identify, in a consolidated fashion, pertinent issues affecting the BOP device reliability, particularly so in a post-Macondo era. Eighty-seven (87) documents expounding these challenges between the years 1980 and

2021 were systemically reviewed. Major challenges and issues associated with the device design, reliability analysis, testing, deployment as well as operability and maintainability were identified. These issues are further discussed in the paper as they are deemed critical, not only affecting the safe and proper functioning of the BOP but also incurring significant capital expenditure (CAPEX) and operating expenditure (OPEX). The findings from critical review of literature include the following:

- Reduced design, installation and operational costs as well as increased safety and better reliability are all benefits that can be accrued from critical assessments of the identified challenges.
- There has been increased attention, particularly after and as a result of the Macondo disaster on the safety of subsea BOPs.
- Some BOP subsystems were found to be more failure prone than others with annular preventer, control pods and LMRP connector requiring greater maintenance effort.
- Active redundancy has been applied to the BOP system and its components to enhance the reliability characteristics of the system.
- Advanced reliability analysis techniques such as Petri Net (PN),
- Bayesian network (BN), Markov modelling and their different variations have been recognized to overcome the drawbacks of conventional reliability assessment techniques such as FTA and FMEA.

2.6 References

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3 DEVELOPMENT OF IMPLEMENTATION FRAMEWORK AND COST BENEFIT ANALYSIS FOR CONDITION BASED MAINTENANCE IN SUBSEA BLOWOUT PREVENTERS

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Statement of contributions:

Tobi Elusakin conducted the literature review, developed the framework, drafted and critically reviewed the manuscript. Mahmood Shafiee provided supervision and critical review of the manuscript before submission. Tosin Adedipe also reviewed and commented on the manuscript before submission.

Abstract

With the steadily growing demand for energy in the world, oil and gas companies are finding themselves facing increasing capital and operating costs. To ensure the economic viability of investments and improve the safety of operations, oil and gas companies are promoting their asset integrity management (AIM) systems. In the past, the oil and gas industry adopted reactive maintenance regimes, which involved recertification, testing and repair of faulty equipment while trying to achieve minimum downtime. As technology becomes more affordable, operators have been better able to carry out improved failure diagnosis, prognosis and prediction. As a result of this, condition-based maintenance (CBM) is being adopted more and more as the preeminent maintenance regime for oil and gas equipment. The blowout preventer (BOP) is one of the most expensive and safety critical drilling equipment in the oil and gas industry. However, there have been very few studies and best practices about how to implement a CBM solution and what its economic added value can be. This paper proposes a V-model based architecture for designing a CBM solution in BOP systems. It also presents a framework to perform an economic feasibility analysis of implementing CBM in subsea oil and gas production systems, with a particular focus on blowout preventers (BOPs). As a result of the model proposed, gaps in implementation are identified and all the hardware, software and training

requirements for implementing the CBM solution in BOP systems will be outlined in detail. Our proposed CBM framework will help BOP operators and maintenance personnel make cost savings through less repairs and replacements and minimal downtime.

3.1 Introduction

As the demand for energy in our world today continues to rise, oil and gas companies find themselves facing increasing capital and operating costs. This is as a result of scarcity of conventional reserves, the complexities associated with extracting and processing unconventional reserves located in ultra-deepwater environments, and the need to enhance recovery of mature sources. To ensure the economic viability of investments and improve the safety of operations, oil and gas companies are promoting their asset integrity management (AIM) systems (Rahim *et al.*, 2010). According to Health and Safety Executive (2007), the AIM involves making sure that the resources, systems and people delivering integrity are all in place and will perform their intended functions when required over the life cycle of the asset.

Though the implementation of CBM is already firmly established in other industries such as transport, manufacturing and aerospace, it still has a long way to go in the offshore oil and gas industry. In the past, the oil and gas industry adopted reactive maintenance regimes which involved recertification, testing and repair of faulty equipment while trying to achieve minimum downtime. In this regime, no efforts whatsoever are taken to predict the equipment's condition or determine its remaining useful life (RUL) and as a result of this, the costs associated with the reactive maintenance regime are quite high (Shafiee *et al.*, 2019). Given that the selected maintenance strategy should normally support the business goals (Markeset *et al.*, 2013), it is understandable that oil and gas companies are now moving further away from the reactive maintenance regime and more towards condition-based maintenance (CBM).

Due to the capabilities of newer, more affordable technologies which allow operators diagnose faults and prognose failures, CBM is being increasingly adopted as the preeminent maintenance regime for oil and gas equipment

(Telford *et al.*, 2011). CBM is a type of preventive maintenance strategy primarily based on the condition of the equipment. Rather than performing maintenance after the equipment failure or at a specified time interval, maintenance is performed when the equipment's condition indicates so. CBM helps to eliminate catastrophic failures, reduce maintenance and repair costs, increase equipment running time and efficiency, and ensure enhanced safety assurance (Mutlu *et al.*, 2018). Time-based maintenance (TBM), which is another subset of preventive maintenance, has a lower initial investment requirement compared to CBM, but incurs considerably higher operating cost which makes it less cost-effective (Gugaliya and Naikan, 2019). The benefits of CBM to offshore oil and gas industry include the enhanced asset availability, reduction in maintenance task costs, increased equipment running time and enhanced safety assurance.

A brief review of the literature reveals that there have been very few studies and best practices about how to develop a CBM solution and what specific monitoring techniques and devices will be required to implement it for blowout preventer (BOP) systems. There have also been very few studies conducted surrounding the financial feasibility of implementing CBM. The subsea BOP, due to the important role it plays in ensuring the safety of drilling personnel, equipment and environment, is considered one of the most expensive offshore drilling systems to maintain (Sattler *et al.*, 2009, Cai *et al.*, 2012). Contrary to common perception, BOPs are not the primary means of well-control. The well is controlled first and foremost by the hydrostatic pressure provided for the weighting of the drilling mud to counterbalance pressure from the reservoir (Brandão Martins *et al.*, 2018). However, the BOP is accurately understood to be the last line of security against erratic well pressure and eventually well blowout (Sattler, 2013).

This paper, to the best of the authors' knowledge, presents the first attempt of designing a CBM implementation framework in BOP systems based on a V-model architecture. A roadmap is proposed to highlight technical and technological gaps in implementing CBM policy for BOPs. As a result, all hardware, software and training requirements to implement the solution are identified and discussed in detail. These requirements are all gleaned from review

of literature and the current state of maintenance in the industry. Furthermore, this study elaborates on the first step in the V-model roadmap by applying cost benefit analysis (CBA) methods to determine economic feasibility of implementing and adopting a CBM regime for subsea oil and gas production systems. Our analysis takes into account both the costs associated with CBM implementation (including acquisition, installation, and operation and maintenance (O&M) costs) and the benefits which are accrued from implementing CBM over the lifetime of the subsea BOP (such as increased revenue and reduced repair costs). The proposed methodology is validated with the adoption of a real condition monitoring system (CMS) in a modern subsea BOP system. It is expected that the proposed CBM implementation framework and feasibility analysis will help BOP operators and maintenance personnel make cost savings through less repairs and replacements and minimal downtime.

The organisation of the paper is as follows. Section 3.2 reviews maintenance evolutions in the offshore energy sector as well as CBA techniques, with CBM as the major focus. In section 3.3, a model for implementing CBM is proposed after which hardware, software and training requirements for CBM implementation in BOPs are discussed. Section 3.4 then presents the CBA framework and section 3.5 concludes the study and suggests options for further research.

3.2 Research Background

3.2.1 Maintenance evolutions in the offshore energy sector

Maintenance signifies the efforts performed throughout the life cycle of a system or component to keep it in or return it to its intended original working state (BSI, 2010). There are two major ways in which maintenance can be performed – maintenance done after the malfunctioning or breakdown of the equipment, known as corrective maintenance, and maintenance done to prevent breakdown of equipment, known as preventive maintenance (BSI, 2010). Figure 3.1 shows a graphical representation of the different maintenance strategies developed for offshore energy assets.

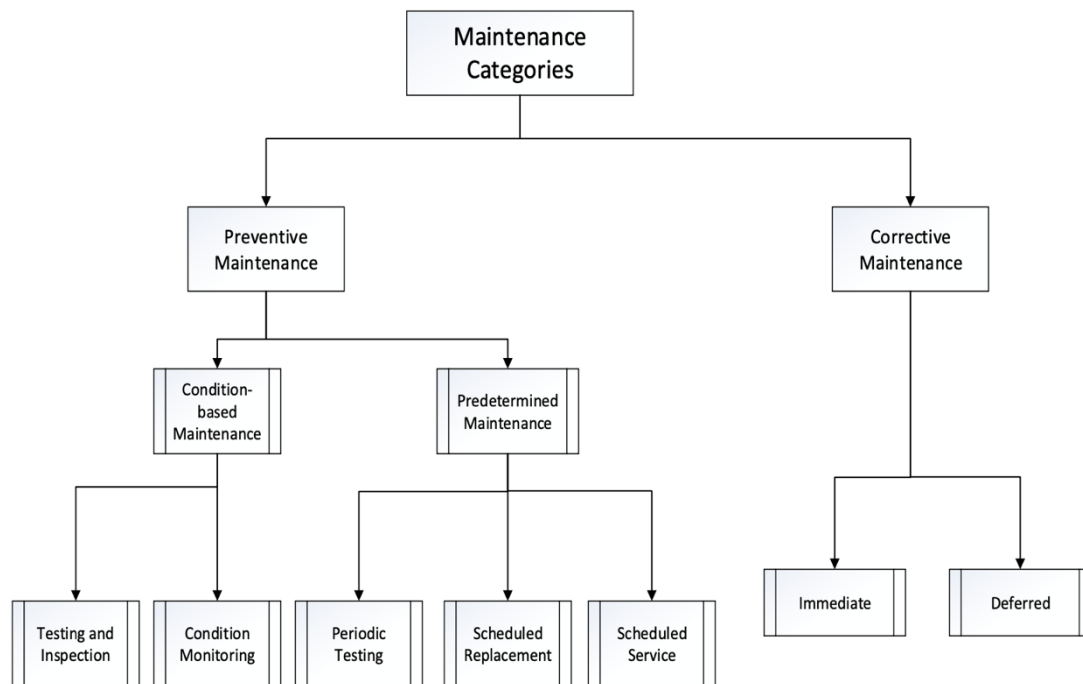


Figure 3.1 Maintenance categorisation (ISO 14224, 2016)

3.2.1.1 Corrective maintenance (CM)

Corrective maintenance ranges from standard repair actions undertaken when an equipment fails to outright replacement of components. When only *minimal repair* is done, it can be said that the equipment is being restored to the condition it was in right before it failed, or “as bad as old”. When *renewal* is performed on the faulty equipment, it can be said that the equipment is being restored to the condition it was in when it began operation, or “as good as new”. In between minimal repair and renewal is where the concept of *imperfect repair* comes in, which is where most repair actions fall into (Bengtsson, 2004a). The concept of imperfect repair is considered in Cai *et al.*, (2013) where the reliability of a subsea BOP is analysed using dynamic Bayesian network (DBN) with and without the consideration of preventive maintenance respectively.

3.2.1.2 Preventive maintenance (PM)

Preventive maintenance includes all actions (service, repair, component replacement) performed for the purpose of avoiding equipment failure (Bengtsson, 2004b). These actions are applied in several industries to help

manage asset degradation rate and mitigate against expensive failures (Shafiee and Finkelstein, 2015). PM can be done in two ways. On the one hand, it can be done in accordance with a predetermined time schedule when it is necessary. This is known as time-based maintenance. Here, the maintenance tasks are conducted after a unit of time in use or in accordance with certain dates. On the other hand, preventive maintenance can also be performed by keeping track of usage patterns of machines. This is known as use-based maintenance (Shafiee et al., 2016). In this case, the maintenance tasks are carried out after a number of times that an equipment has been used or after a number of miles in operation.

3.2.1.3 Condition-based maintenance (CBM)

CBM, according to ISO 14224 (2016), is defined as a kind of PM in which the maintenance decisions are made based upon the condition of physical assets. Based on the concept of condition monitoring, CBM has come a long way over time. Monitoring, in its early days consisted of human beings inspecting equipment and machinery via primitive methods such as sense of smell, touch, taste and vision. Over time, monitoring technology has evolved to the use of sensors to gather data as machines have become more complex and systems more cutting-edge (Kallevag, 2015).

CBM is the application of condition monitoring to analyse the current operating state of a machine, uncovering irregularities before they become irreversible and subsequently devising an appropriate maintenance schedule with that knowledge (Bengtsson, 2004). It involves actions undertaken before failure to ensure that a system or component remains in operation. The CBM plan provides better maintenance-action options than time- or use-based maintenance and is a suitable way to monitor and evaluate how a system's performance degrades gradually, in particular when operating in harsh environments like deepwater offshore (Hwang, 2015).

The two major building blocks to CBM are “diagnostics” and “prognostics”. Diagnostics, which entails finding the root cause of machine failure after the failure has occurred, involves three sub-processes: fault detection, fault isolation and fault identification. Prognostics on the other hand, deals with fault prediction.

It is done to recognise when a fault in a machine is imminent and estimate how likely it is that the fault will occur. In trying to attain a state of zero-downtime, prognostics is the more efficient route to take with regards to equipment maintenance; however, in the near-inevitable event of a fault occurring, diagnostics will prove very useful and as such cannot be ignored (Jardine *et al.*, 2006).

3.2.2 CBM for BOPs

In the wake of the Macondo incident in 2010, the offshore industry has become more pressured to change its asset integrity management (AIM) approach from the standard interval-based maintenance to CBM (Turner and Loustau, 2015). However, this is still in its infancy and very few studies on how CBM has been implemented have been performed. These studies have ranged from the subject of regulatory oversight to model development for condition monitoring. McKay *et al.* (2012) discussed the use of a dashboard and the traffic light system to monitor the health of the subsea BOP and communicate the health status to rig operators. Carter *et al.* (2014) conducted a comprehensive review on the lack of activities constituting regulatory oversight of BOP safety and made recommendations on how this can be changed through real-time condition monitoring. Turner and Loustau (2015) tested fibre optic strain gauges as a monitoring technology on BOPs and found it a viable option for operators. A condition and performance monitoring (CPM) solution was proposed by Mutlu *et al.* (2018) to detect the degradation of a BOP ram-function and determine its origin and magnitude. Xiu *et al.* (2015) developed a lifetime prognosis approach based on the Weiner process to estimate the lifetime of a BOP valve.

The BOP, being one of the most safety- and mission-critical drilling equipment would provide a promising case for the application of CBM to offshore drilling systems. Toward this end, a recommendation was made by the Transportation Research Board (2016) to the Bureau of Safety and Environmental Enforcement (BSEE) that the American Petroleum Institute (API), original equipment manufacturers (OEMs), drilling contractors, and trade associations work together

to create a pilot project about the applications of CBM to a BOP with the main aim of developing an API recommended practice publication.

As a failure starts to develop in the BOP, the specific indicator for that failure mode will start to change to allude to the developing situation. This is the point P within the PF curve as shown in Figure 3.2. If the indicated failure is allowed to continue to develop, the curve reaches the point F (functional failure point), where asset or component failure has occurred.

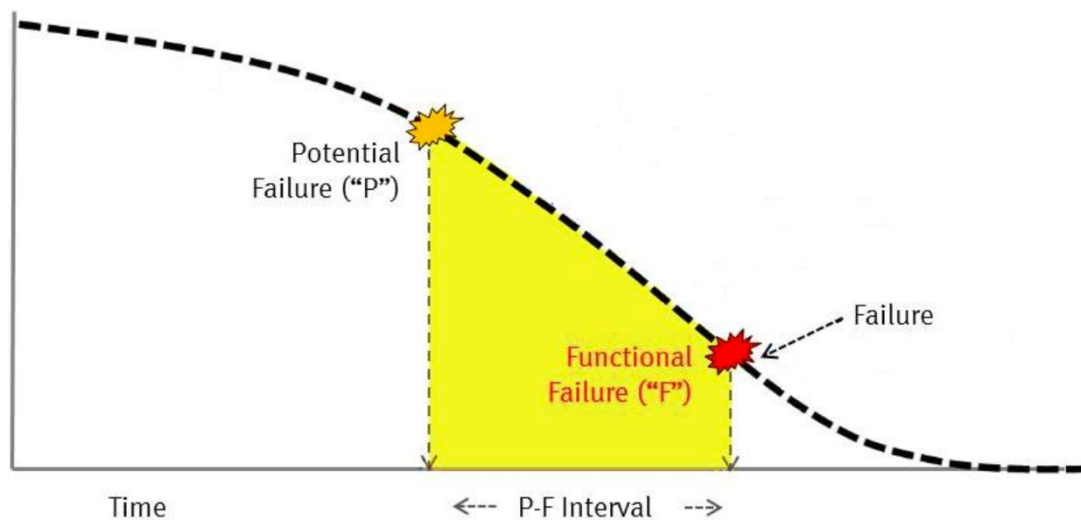


Figure 3.2 Typical P-F curve (Bousdekis *et al.*, 2015)

According to Mutlu *et al.* (2018), roughly 50% of offshore rig downtimes are caused by BOP failures. Therefore, implementing CBM in BOPs can be highly advantageous as the benefits almost assuredly cascade on to the drilling equipment. These benefits include:

- Elimination of loss in revenue
- Savings in maintenance costs
- Increase in equipment running time
- Reduction of time and cost of repair
- Increase in efficiency
- Enhanced safety assurance

3.2.3 Cost-Benefit Analysis

The primary purpose of a CBA is to determine if a proposed action or endeavour is financially viable/profitable (Børresen 2011). It is a tool for analysing investments/projects to determine if they are financially viable. In cases where there are limited resources, CBA is a tool to determine which projects should be chosen (Mishan and Euston, 2007). The process for CBA involves determining investment alternatives and base case, determination of costs and benefits, selection of required financial parameters, data collection, calculation of the present value of benefits and costs, application of chosen CBM technique and finally, acceptance or rejection of an investment alternative (Animah *et al.*, 2018). According to Kull *et al.* (2013), one major benefit of a CBA is its clear and thorough analysis of profit and loss, making investment decisions more transparent. Another benefit of CBA is the compatibility of its result to actual market tools (Shafiee *et al.*, 2019). Different CBA techniques include benefit cost ratio (BCR), internal rate of return (IRR), net present value (NPV) and payback period. In what follows, these techniques are briefly explained.

3.2.3.1 Net Present Value

The NPV of an investment option can be determined by deducting the present value of the cash invested from the present value of the net cash receipt. A positive NPV value signifies a positive return on investment and vice versa (British Standard Institute, 2001). This is often considered the most preferred criteria for decision-making on a proposed investment. NPV can be calculated as (Gugaliya and Naikan, 2019):

$$NPV = \sum_{t=1}^T \frac{C_t}{(1+i)^t} - C_0 \quad (3-1)$$

where i is the required rate of return per year.

3.2.3.2 Internal rate of return

According to British Standard Institute (BSI) (2001), IRR is defined as the discount rate at which the net present value is equal to zero ($NPV = 0$). The IRR is calculated using the following equation:

$$0 = NPV = \sum_{t=1}^T \frac{C_t}{(1 + IRR)^t} - C_0 \quad (3-2)$$

where C_t represents the net cash inflow after year t ; T represents the project duration in years; C_0 is the initial investment expense and represents the number of time periods. If the IRR of a proposed investment option is higher than the minimum internal rate of return (MIRR), this signifies that it will provide a higher return on investment than the required minimum.

3.2.3.3 Benefit Cost Ratio

BCR is the ratio of the present value of benefits to the present value of investment costs. An investment option is only considered financially worthwhile if the BCR is greater than 1. If there are multiple investment options and only one can be selected, then the option with the highest BCR is selected (Animah *et al.*, 2018). The BCR can be calculated using the following equation:

$$BCR = \frac{PVB}{PVC} = \frac{\sum_{t=1}^T \frac{B_t}{(1 + i)^t}}{\sum_{t=1}^T \frac{C_t}{(1 + i)^t}} \quad (3-3)$$

where PVB is the present value of benefits; PVC is the present value of expenses, i signifies the rate of return per year, C_t signifies costs in year t and B_t signifies the benefits in year t .

3.2.3.4 Payback Period

This can be defined as the period of time in which a particular undertaking is expected to recoup its initial investment. This is a quick and easy way to determine the profitability of an investment option. Payback period can be calculated using the following equation:

$$PP = \frac{C_0}{\text{Yearly } NCI} \quad (3-4)$$

where PP represents payback period and NCI represents net cash inflow. This method, however, ignores the net cash flow after the payback period has elapsed (Belyadi *et al.*, 2016).

3.2.4 Cost-Benefit Analysis in CBM

The offshore energy industry, in the aftermath of the Macondo incident, has found itself under more pressure to move from the standard time-based maintenance to implementing CBM (Turner and Loustau, 2015). As this is still in its infancy, however, studies on CBM implementation which focus primarily on offshore oil and gas systems are few and far between. According to Thurston (2001), a CBM component contains seven modules: data acquisition, (sensors), signal processing, condition monitoring, health assessment (diagnosis), prognosis, decision support and presentation. These modules all factor into cost determination for CBA. The performance of a CBA is one of the prerequisites for implementing any form of CBM strategy (Amin 2016). This is backed up by ISO 17359:2018 (British Standards Institute 2018) in which the very first step to perform in CBM implementation is the CBA.

There are a number of studies which have investigated the economic costs and benefits of implementing CBM and condition monitoring systems in various industries. Pertinent research on cost-benefit analysis of CBM can be seen to go back as early as (Rajan and Roylance, 2000), in which a mathematical model was developed and proposed to predict the cost effectiveness of different maintenance programmes for batch process equipment in the pharmaceutical industry, with a particular focus on the economic analysis of practicing CBM. In Hess *et al.*, (2001), both the costs and benefits of different CBM technologies were analysed in order to make a decision as to the most effective technology. Rastegari and Bengtsson (2015) investigated how the cost effectiveness of employing CBM in the manufacturing industry can be analysed in order to avoid

poor applications; while in the nuclear energy industry, IAEA (2007) examined the implementation strategies for CBM in nuclear power plants.

The offshore environment provides its own particular set of challenges which make implementation of CBM more difficult than in other industries. As a result of this, accurate determination of the costs and benefits of implementing CBM as a maintenance strategy is of immense importance. In Børresen, (2011), an offshore oil and gas separator was used as a case study for the implementation of CBM in conjunction with Integrated Operations (IO). A cost-benefit analysis, which took both reliability and financial perspectives into account, was performed on the implementation of the CBM programme in order to justify its use.

3.3 A Roadmap for Applying CBM to BOPs

In order to apply CBM to a complex system such as the BOP, a systems engineering approach such as the V-model is recommended. The V-model is used primarily as a means to deduce system requirements and implement the resultant system. The V-model is designed to help in understanding the intricacies associated with developing a complex system. Its purpose is to improve the effectiveness and efficiency of the CBM system development. Our developed V-model architecture for CBM of BOPs is illustrated in Figure 3.3. To develop this model, extensive review of literature pertaining to condition monitoring procedures and personnel requirements was performed. Literature on the subject of the V-model was also reviewed to determine how it can be applied to CBM of BOP.

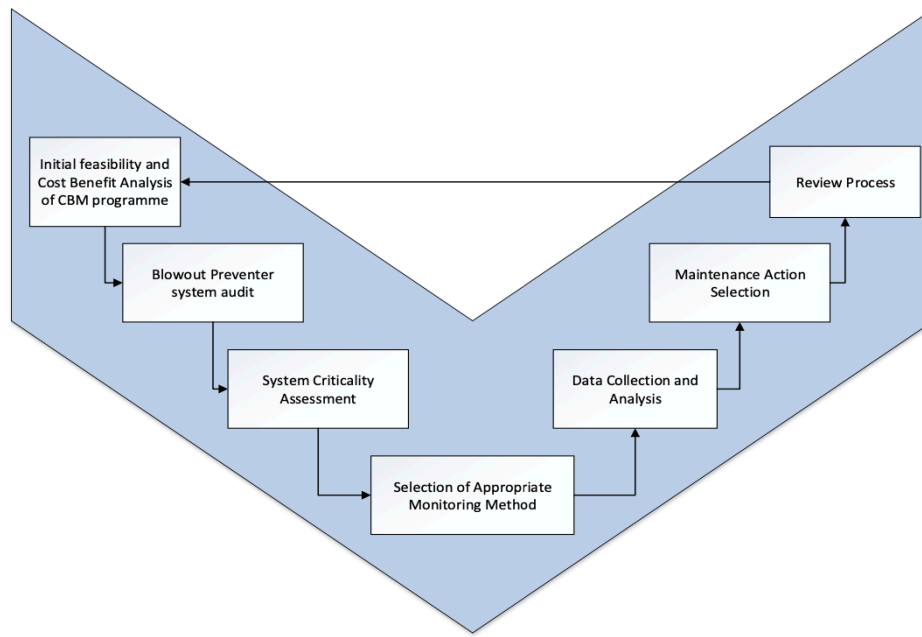


Figure 3.3 A V-model based architecture for condition-based maintenance of BOPs

In what follow, the steps of the presented framework are described in details:

Feasibility assessment and cost-benefit analysis

The first step of the model is to perform an initial economic feasibility assessment and cost-benefit analysis (CBA) by taking into account the costs incurred when there is no condition monitoring system in place, the costs incurred as a result of the implementation of CBM and the benefits gained by the implementation of CBM. Techniques which can be used to perform this economic analysis include the Net Present Value (NPV), Benefit-Cost Ratio (BCR) and Internal Rate of Return (IRR). This helps to identify the appropriate key performance indicators (KPIs) for measuring the effectiveness of the proposed CBM programme.

System Audit

An audit of the entire BOP system should then be performed to identify those critical components that can be monitored, their functions, the data to be measured, and the monitoring techniques to be employed. According to Holand and Awan (2012), the relevant subsystems of a BOP to be monitored include the annular preventer, connectors, flexible joint, ram preventer, choke and kill valves,

choke and kill lines and the BOP control system. The purpose of the audit is to also determine what the operating conditions or range of operating conditions are for each subsystem. This helps to create a baseline through which performance anomalies can be detected.

System criticality assessment

A failure mode, effect and criticality analysis (FMECA) or a hazard and operability (HAZOP) study is then recommended so as to list the BOP components in order of priority and their corresponding failure criticality. A study performed by Holand and Awan (2012) encompassing 259 wells and 156 BOP related failures showed that the highest contributor to BOP failures is the control system with 45% of the total number of failures. It also gave detailed insight into the failure modes of each relevant BOP subcomponent as shown in Table 3.1. Another study by the BSEE (2013) determined that the most important, the most frequently occurring and the hardest to detect BOP component failures are the blind shear rams, electro-hydraulic control systems and the auto-shear system respectively.

Table 3.1 Failure modes of BOP major components. Source: (Palem, 2013)

BOP Component	Failure Mode
Annular Preventer	Failed to close
	Failed to fully open
	Failed to open
	Internal hydraulic leakage
	Internal leakage through a closed annular
Hydraulic Connector	External leakage to environment
	Failed to lock
	Failed to unlock
	Spurious unlock
Ram Preventer	External leakage
	Failed to close

	Failed to fully open
	Failed to open
	Internal leakage through a closed ram
Choke and Kill Valve	Internal leakage of lower kill valve
	Leakage of upper inner choke valve
	Leakage of lower outer kill valve
Choke and Kill Line	BOP attached line external leakage
	Jumper hose line external leakage
	Riser attached line external leakage
BOP Control System	Loss of all functions in both pods
	Loss of all functions in one pod
	Loss of one function in both pods
	Loss of several functions in one pod

Selection of appropriate monitoring methods

The appropriate measuring methods should now be chosen, and these must take into account the accuracy of the monitored parameters, the monitoring interval, data acquisition rate, operating conditions during monitoring, measurement locations, baseline data, preliminary alarm benchmarks, and feasibility of monitoring. Monitoring methods which may be used for BOPs include vibration analysis, infrared thermography, acoustic emission analysis, and ultrasound analysis. Table 3.2 presents a matrix of the condition monitoring techniques against BOP components as well as each technique's advantages and disadvantages.

Table 3.2 Evaluation of BOP monitoring techniques

	Condition Monitoring	BOP Components						Advantages	Disadvantages
		BOP Control System	Annular Preventer	RAM Preventer	Hydraulic Connectors	Choke & Kill Valves	Choke & Kill Lines		
Vibration Analysis	✓	•	•	•	•	•	•	-Reliable	-Costly -Invasive
Infrared Thermography	✓	•	•	•	•	•	•	-Non-intrusive -Provides results quickly	-Radiometric sensing susceptible to error
Acoustic Emission	✓	•	•	•	•	•	•	-Non-intrusive -Provides real-time information	-Susceptible to attenuation -Can be affected by operational ambient noise
Ultrasound Analysis	✓	•	•	•	•	•	•	-Non-intrusive -Provides results quickly	-Requires thorough understanding of ultrasound

Data acquisition and analysis

Parameters such as temperature, noise, and vibrations are measured and the data from these measurements are collected and analysed using sensors and data analysis software respectively. The quality of the data collection is paramount here as there are a number of factors that can contribute to poor measurements. It is recommended that the collected data to be compared to the values that constitute the alarm criteria so as to more easily determine whether maintenance action is necessary or not. If an anomaly is in fact detected, diagnosis and prognosis can be performed. Diagnosis is conducted to determine the cause of the fault and prognosis is performed to predict the fault progression determine the estimated time to failure. Table 3.3 shows various data items which are required for CBM of BOPs.

Table 3.3 Data requirement table for CBM process for BOPs

Type of Data	Required Information	Data Source
Design data	System design requirements	Operator/Manufacturer
	Component design requirements	Operator/Manufacturer
	Standards and codes	Standard documents (e.g., BSI, API)
	Material Specification	Operator/Manufacturer
	Design life calculations	Operator/Manufacturer
Cost data	Cost of implementing CBM	Operator
	Cost of maintenance without CBM	Operator
	Revenue from uninterrupted production	Operator
Operational data	Operational parameters (e.g. Noise, temperature, vibrations)	Operator
	Reliability data	Operator
	Inspection and Maintenance data	Operator
	Condition monitoring data	Operator

Maintenance action selection

Following the data acquisition and analysis, the appropriate maintenance action or decision should be determined based on the level of confidence in the fault diagnosis and prognosis. Selection of the appropriate maintenance action can be a complex endeavour as there are always competing goals and criteria to consider. Shafiee (2015), therefore categorised it as a complex multi-criteria decision making (MCDM) problem. MCDM methods which can be used to select a maintenance action include simple additive weighting (SAW), technique for order of preference by similarity to ideal solution (TOPSIS), elimination and choice translating reality (ELECTRE), analytic network process (ANP), etc.

Typical maintenance decisions include: no action, reduce measurement intervals, perform corrective maintenance, shut down the machine.

Following the completion of whatever maintenance action is chosen, the activities should be preserved as historical record for the purpose of assisting in future diagnosis and prognosis. In order to confirm that the diagnostic or prognostic action taken is correct, it is also beneficial to inspect the maintained components.

Programme review

Given that CBM of BOP is still in its infancy, there is a high chance that some monitoring techniques and equipment may be considered too expensive, complicated or unfeasible to apply at the time. It is therefore recommended that such techniques and equipment be re-evaluated as they can become feasible and even beneficial as time and technologies advance. In a similar vein, the processes, hardware and software used in the applied CBM programme should be reviewed so as to identify and remove anything no longer seen as necessary.

Translating different technologies and techniques proposed in previous research proves difficult as the decision to implement CBM in subsea environment must take into account the complexities that come with the operating environment as well as the need for the best available and safest technology (BAST) (2016). Based on literature review, the gaps associated with implementing CBM in blowout preventers fall into three broad categories: hardware gaps which include sensor and signal processing equipment; software gaps which encompass modelling and analysis; and training gaps, which encompass the personnel and knowledge required to implement any chosen CBM strategy. As a result of these gaps, requirements for implementation of CBM tailored to the aforementioned broad categories are presented in the next section.

3.3.1 Requirements for Implementation of Condition-based Maintenance in Blowout Preventers

Taking full advantage of CBM for BOPs will require the fulfilment of hardware, software and training requirements. Suitable hardware is needed to be able to

monitor, record and transmit data which describes the condition of the equipment. Software is also required to transform collected data into information upon which maintenance decisions can be made by maintenance professionals. Lastly, personnel which are specially trained to assess and interpret condition data and have the requisite knowledge and skills to make the right maintenance- related decisions.

The components which will be monitored as part of the BOP are the annular preventer, the LMRP connector, the wellhead connector, flexible joint, ram preventer, choke and kill lines, choke and kill valves and the BOP control system.

3.3.1.1 Hardware Requirements

For a complex system such as BOP, hardware requirements for CBM need more than just the use of sensors to measure the performance. Hardware for condition monitoring of a blowout preventer require sensors attached to it which collect and send data about its operational condition and performance to a monitoring station. The monitoring station performs real-time analysis of the data collected and detects if there are any problems with the performance of the BOP (Palem, 2013). The monitoring station can be part of the same network as the sensors, an example of which is a rig-based engineering workstation (EWS) described by Mckay *et al.* (2012) or it can be in a remote location a great distance away from them. Sensors utilized for monitoring can be installed as permanent entities, semi-permanent entities, portable measuring instrumentation or the use of sampling fluids for both local and remote analysis (ISO 17359, 2018).

Given that the BOP is a system with multiple different components which need to be monitored, different parameters will inherently need to be measured. These parameters include noise, temperature and vibrational frequencies, etc. It means that different types of sensors are required to monitor these parameters and collect data. When measurements indicate levels beyond the ordinary, these are taken as symptoms of issues such as internal and external leaks, dents, faults, cracks, friction, corrosion and hydraulic resistance.

Sensors which can be used for vibration analysis include Piezoelectric (PE) accelerometers for measuring acceleration as a result of shock or vibration; eddy current proximity sensors for measuring displacement; and moving-coil velocity sensors for measuring velocity (Bogue, 2013). Piezoceramic sensors are traditionally the go-to options for acoustic emissions; however, optical fibre Bragg gratings (FBG), in recent times have emerged as a suitable alternative (Innes *et al.*, 2017). The infrared thermography technique makes use of an uncooled microbolometer as a sensor. These have become widely used as a result of recent technological advancements, increased affordability and its ability to provide quick ways to scan systems with a large number of components (Presley, 2018). Just developed by Baker Hughes General Electric (BHGE), is the NDT BOP Inspection System which uses digital “fingerprinting” powered by 4-D scanning. Robotics, analytics and phased array ultrasonic testing are utilised to create a 4-D rendering of the BOP system and this becomes the baseline for the asset condition at any other point of its operation (ISO 18436, 2012).

3.3.1.2 Software Requirements

The software used for CBM plays an immensely important role in capturing and processing vast amounts of data coming from the subsea BOP. For any software to be used in condition monitoring, and by extension, CBM of BOPs, it is required to have the capability to analyse the data collected and transform it into information which helps determine if a fault has in fact occurred with the component being monitored. In certain cases, highly advanced software can recommend the maintenance actions to take after a fault has been detected. With every BOP component being monitored, there is always the potential for false positives. It is therefore recommended that the software applied in the CBM programme have the capacity to clean data. Examples of software which can be used for this purpose include Measuresoft: ScadaPro; Measuresoft: DrillPro; NOV: RigSense® Information Systems; Rig Minder; and Schlumberger: Wellwatcher (BSEE, 2014).

3.3.1.3 Training requirements

The effectiveness of any CBM programme, no matter how sophisticated or brilliant, greatly depends on the capabilities of the personnel involved. When dealing with very complex systems like BOPs, adequate knowledge is essential for implementation of CBM. This means sufficient training must be provided for personnel who perform the essential condition monitoring activities, personnel who help detect errors, faults and failures and personnel who recommend maintenance actions.

The training requirements for the application of CBM to BOPs are categorised based on the non-intrusive monitoring techniques which apply to this system and its components. Those techniques include vibration analysis, infrared thermography, acoustic emission analysis, and ultrasound analysis (ISO 18436, 2012). Before they can be authorised to take any CBM actions, workers must have the required background education, training and experience in BOP condition monitoring and diagnostics. Table 3.4 below discusses the different subject areas which CBM workers should be trained on based on the techniques which will be used to monitor the condition of the system. Each technique also has different levels of qualifications which require different numbers of hours of training, however, this is not discussed within this paper.

Table 3.4 Training requirements for condition-based maintenance of blowout preventers

Subject Areas	Monitoring Techniques			
	Vibration Analysis	Acoustic Emission	Infrared Thermography	Ultrasound
Principles of Vibration	✓			
Data Acquisition	✓	✓		✓
Data Storage and Management				✓
Signal Processing	✓	✓		
Principles of Ultrasound				✓

Condition Monitoring	✓	✓	✓	✓
Applications to Machine Systems				✓
Condition Monitoring Programme Design			✓	
Condition Monitoring Programme Implementation			✓	✓
Condition Monitoring Programme Management			✓	
Image Processing			✓	
Principles of Acoustic Emissions		✓		
Rotor and Bearing Dynamics	✓			
Fault Analysis	✓	✓		
Principles of Infrared Thermography			✓	
Personal safety	✓	✓		✓
Corrective Action	✓	✓	✓	✓
Diagnostics and Prognostics			✓	
Equipment Knowledge	✓	✓		✓
Acceptance Testing	✓			
Equipment testing and Diagnostics	✓			
Reference Standards	✓			
Reporting and Documentation	✓	✓	✓	✓
Fault Severity Determination	✓	✓		✓

3.4 Cost-benefit analysis model for Implementing CBM

3.4.1 Costs of implementing CBM

It is essential for all estimates on the costs of implementing CBM be as accurate as possible. CBM costs can be single, one-time expenses such as initial acquisition and installation costs as well as regular expenses such as those made for operation and maintenance (O&M) (Børresen 2011). The cost elements for implementing CBM are defined below:

3.4.1.1 Acquisition of CMS

The implementation of a CBM system requires a range of hardware and software components which may be purpose-built for the system in question or off-the-shelf components (Lebold *et al.*, 2002). Hardware components acquired for CBM implementation include sensors attached to the equipment offshore to monitor the condition of the system and data processing stations which can be on the same network as the sensors (rig-based) or located onshore. Due to the multi-component nature of the offshore drilling systems, different types of sensors need to be acquired to measure a host of parameters such as vibration, temperature and noise (Elusakin *et al.*, 2019). Health management software used for detailed analysis of the data collected using techniques such as overall trending and pattern matching will also have an initial acquisition fee. Both hardware and software must meet operational needs and must be able to seamlessly integrate into the overall maintenance structure (Gillespie 2015). The cost of acquisition of CBM components given by the equation:

$$C_{aq}^{Total} = C_{aq}^H + C_{aq}^S + C_{aq}^T \quad (3-5)$$

where C_{aq}^H is the cost of hardware acquisition, C_{aq}^S is the cost of software acquisition, and C_{aq}^T is the cost of training acquisition.

Acquisition of CBM hardware involves sensor, signal processor and server acquisition. Therefore,

$$C_{aq}^H = (N_{sensor} \times C_{sensor}) + (N_{sig.proc} \times C_{sig.proc}) + (N_{servers} \times C_{servers}) \quad (3-6)$$

$$C_{aq}^S = C_{license/yr} \times t_{licensing} \quad (3-7)$$

$$C_{aq}^T = N_{Training\ hours} \times C_{training/hour} \quad (3-8)$$

where N_{sensor} represents the number of sensors, $N_{sig.proc}$ represents the number of signal processors, $N_{servers}$ represents the number servers, $N_{Training\ hours}$ represents the number of training hours, C_{sensor} represents the cost of sensors, $C_{sig.proc}$ represents the cost of signal processors, $C_{license/yr}$ represents the cost per year of licensing software, $t_{licensing}$ represents the duration of software license in years and $C_{training/hour}$ represents the cost of training per hour.

3.4.1.2 Installation of CMS

Both the hardware and software used for CBM require installation. Installation costs include labour costs, fees paid for tailoring the components to the specific system that requires the CBM and the cost associated with downtime. Downtime costs in this case will depend on how intrusive the installation of the monitoring equipment is, making it of paramount importance that installation be carried out in the design phase or when there is an optimal opportunity (Børresen 2011; Gillespie 2015). Cost of installing CBM components can be given by the following equation:

$$C_{inst} = C_{inst}^{labour} + C_{inst}^{logistics} + C_{inst}^{downtime} \quad (3-9)$$

where C_{inst} is the cost of installation; C_{inst}^{labour} is the cost of hiring labour for hardware/software installation; $C_{inst}^{logistics}$ is the cost of logistics involved in

hardware/software installation; $C_{inst}^{downtime}$ represents the cost of downtime due to installation.

The expenses as a result of labour and production downtime can be calculated using the following equations respectively:

$$C_{inst}^{labour} = l_{rt/day} \times N_{md-inst} \quad (3-10)$$

$$C_{inst}^{downtime} = C_{pl/day} \times N_{dd-inst} \quad (3-11)$$

where $l_{rt/day}$ represents the labour rate per day, $N_{md-inst}$ represents the number of man-days required for installation, $C_{pl/day}$ represents the cost of production lost per day and $N_{dd-inst}$ represents the number of downtime days as a result of installation. Expenses related to logistics involve vessel hire, spare part costs, crew transport and cost of consumables.

The cost of production lost per day, $C_{pl/day}$ can further be calculated using the following equation (Animah et al. 2018):

$$C_{pl/day} = PR_{BOPD} \times C_p \times (1 - A_{NCBM}) \quad (3-12)$$

where PR_{BOPD} represents the rate of production in barrels of oil per day, C_p represents the cost of a unit of production and A_{NCBM} represents the average system availability of the equipment.

3.4.1.3 Operation and Maintenance of CMS

In addition to the initial acquisition and installation costs, there are expenses associated with the operation of the new maintenance regime. This includes provision of personnel training on operation of monitoring systems and complex data analysis; upgrading and maintenance of hardware and recurring licensing costs for health management software. Cost of O&M of CBM components can be given by the following equation:

$$C_{OPEX} = C_{Labour} + C_{Upgrade} + C_{Licensing} \quad (3-13)$$

where C_{OPEX} is the cost of operation and maintenance; C_{Labour} is the cost of labour required for the operation of the CBM system; and $C_{Upgrade}$ is the cost of upgrading hardware.

3.4.2 Benefits of implementing CBM

The benefits of implementing CBM range from the tangible to intangible benefits. Tangible benefits include cost savings from reduced maintenance actions and increased revenue as a result of increased production. Intangible benefits are more difficult to analyse in a traditional cost-benefit exercise as some of the variables considered are less measurable than pure asset performance characteristics (Mobley 2001). Examples include improved overall safety, improved reputation and avoidance of environmental damage. For this CBA, only tangible benefits can and will be considered.

3.4.2.1 Reduction in maintenance costs

CBM involves considerably less maintenance interventions as the incorporation of condition monitoring technology allows for the ability to determine when maintenance is needed based on the condition of the equipment rather than when failure occurs, as is the case with corrective maintenance or when inspections are scheduled, as is the case with preventive maintenance. This is important as the costs of corrective maintenance tasks are, on average, considerably more than maintenance costs for tasks associated with CBM (Saranga and Knezevic, 2001). This benefit also includes reduction in maintenance costs associated with secondary damage as allowing some components to fail can also compromise other components, leading to more repair costs than anticipated. The decrease in number of maintenance actions directly results in a decrease in maintenance cost and can be considered as tangible income. The benefit can be quantified using the following equation:

$$B_{MTC} = (C_{Maint-old} \times N_M) - (C_{Maint-CBM} \times N_M) \quad (3-14)$$

Where B_{MTC} is the total benefit associated with reduction in maintenance task costs, $C_{Maint-old}$ is the maintenance task cost associated with the old

maintenance regime, $C_{Maint-CBM}$ is the maintenance task cost associated with CBM, and N_M is the number of maintenance tasks.

3.4.2.2 Revenue from increased availability

According to Mobley (2001), the incorporation of CBM strategy has also been proven to result in less equipment downtime as a result of failures which in turn leads to increased revenue from production. This can be calculated as:

$$B_{IA} = PR_{BOPD} - (A_{CBM} \times A_{NCBM}) \quad (3-15)$$

Where B_{IA} represents the benefit as a result of increased availability, A_{CBM} represents the system availability when CBM is implemented and A_{NCBM} represents system availability when CBM is not implemented.

The total benefit as a result of implementing CBM can then be calculated as:

$$B_{Total} = B_{MTC} + B_{IA} \quad (3-16)$$

3.4.3 Application case

This section discusses a case study involving a multiplex electro-hydraulic (MUX) subsea blowout preventer which is located on a semisubmersible rig. The BOP contains two annular preventers, eight choke and kill valves, two blind shear rams and four variable pipe rams (Holand and Awan, 2012). The condition monitoring system which has been proposed for this BOP is the Rigsentry CMS, a product of National Oilwell Varco (NOV). The Rigsentry is both DNVGL and ABS certified for monitoring the condition of subsea and drilling services and also consists of all hardware, software and training required for consequential condition monitoring data analysis. It performs prognostic health management and determines precursors to component failures using predictive analysis models. It also creates customised maintenance plans which accurately represent the condition of the BOP. This consequently helps to lengthen the maintenance windows and reduce the expense on spare parts. The NPV and BCR techniques will be used to perform the cost benefit analysis for this application case. The financial and non-financial data used for this study has been accumulated from literature, company databases and expert elicitation. Table 3.5 below shows a

summary of the total costs and benefits which has been used for the cost benefit analysis.

Table 3.5 Case study data (National Oilwell Varco, 2019)

Parameters	Value	Unit
C_{aq}^{Total}	143,500	GBP
C_{inst}	65,500	GBP
C_{Labour}	427,500	GBP
$C_{Licensing}$	123,500	GBP
B_{Total}	932,715	GBP
i	7	%
T	10 years	Years

Based on the data obtained for this case study, the total cost of acquisition and total cost of installation are combined and considered as the total initial investment for CBM implementation. In addition, the annual expenditure for operating the CMS consists of service support, yearly software subscription fee and physical rig inspections.

The NPV for this investment was calculated using Equation (3-1) as £981,508.5. This indicates that the investment in CBM implementation for subsea BOPs is financially beneficial. The BCR was also calculated using Equation (3-3) as 1.77, signifying that the benefits of an investment in CBM for BOPs outstrip the costs.

A sensitivity analysis is conducted to assess the robustness of the analysis performed. This was done by varying the discount rate on both NPV and BCR equations. A 20% variance is applied here as it represents a realistic possible change in the standard interest rate on offshore oil and gas investments. As can be seen in Figure 3.4 and Figure 3.5 respectively, a 20% increase in the discount rate yields a decrease in both the NPV and BCR while a 20% decrease in the discount rate yields an increase in the NPV and BCR.

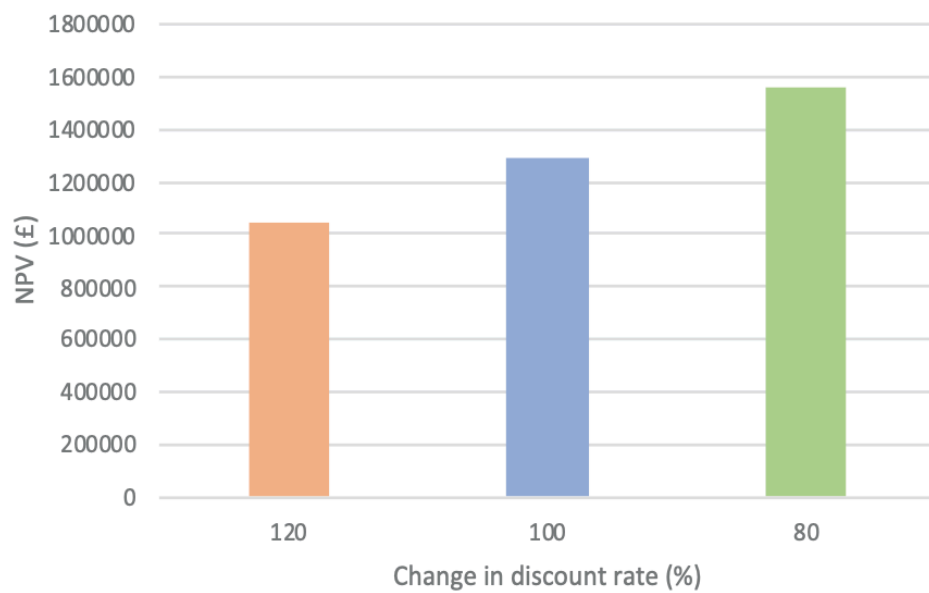


Figure 3.4 Effect of variation in discount rate on NPV

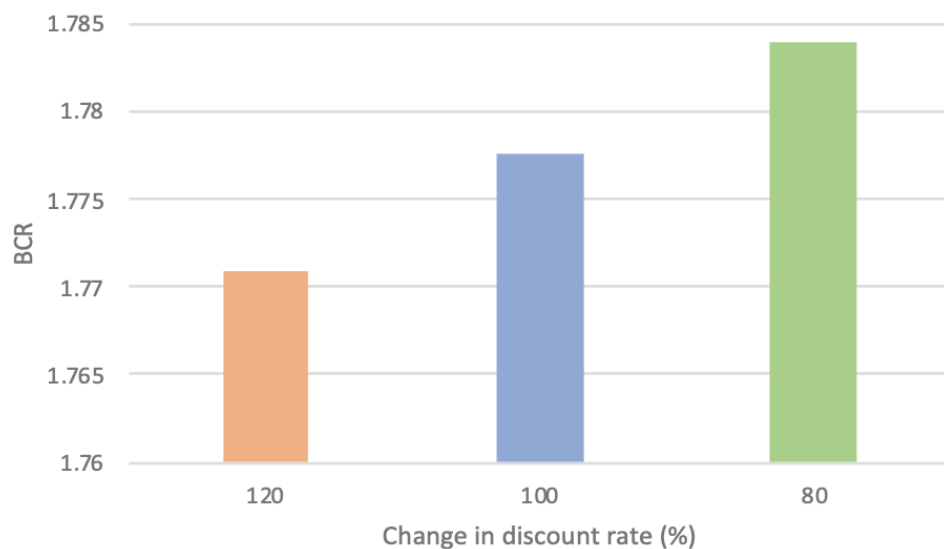


Figure 3.5 Effect of variation in discount rate on BCR

3.5 Conclusions

As the cost of ending drilling operations to evaluate a blowout preventer (BOP)'s condition currently runs over 1 million USD per day, condition-based maintenance (CBM) is needed now to help reduce maintenance and downtime

costs as well as improve safety. In this study, a roadmap towards the implementation of CBM in BOPs was proposed. A model, adapted from the standard V-Model architecture used in systems engineering and development was presented and from this, gaps in CBM implementation were identified. As a result of these gaps, hardware, software and training requirements were identified. The first step of the roadmap, which was a cost benefit analysis of implementing CBM, was also explored. The expenses and benefits associated with the implementation of CBM in subsea BOPs were identified with corresponding equations outlined in detail. The NPV and BCR techniques were applied to a case study with both confirming the economic viability of CBM implementation in subsea BOPs. A sensitivity analysis was conducted to determine the effect of changing the discount rate on the NPV and BCR.

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4 RELIABILITY ANALYSIS OF SUBSEA BLOWOUT PREVENTERS WITH CONDITION BASED MAINTENANCE USING STOCHASTIC PETRI NETS

Tobiloba Elusakin and Mahmoud Shafiee

Statement of contribution:

Tobiloba Elusakin was responsible for study conceptualisation, methodology, software, validation, formal analysis, investigation, data curation, writing the original draft, review and editing, visualisation and project administration. Dr Mahmoud Shafiee was responsible for study conceptualisation, methodology, software, validation, formal analysis, investigation, review and editing, visualisation and supervision.

Abstract

The Blowout Preventer (BOP) has maintained its function as a safety barrier and the last line of defence against oil and gas spills since its development in the early 1900s. However, as drilling and exploration activities move further offshore, challenges pertaining to reliable operation of the subsea BOP systems continue to be a source of concern for stakeholders in the industry. In spite of recent advancements in the reliability analysis of safety instrumented systems (SISs), the research on reliability assessment of BOP is still lacking in some regards. There are gaps in the literature with respect to the incorporation of preventive maintenance (PM) strategies as well as dynamic operating conditions into BOP reliability analysis. To address these gaps, this paper develops an advanced analysis method using stochastic Petri nets (SPN) to estimate the reliability of subsea BOP systems subject to condition-based maintenance (CBM) with different failure modes. The BOP system has been divided into five subsystems which are connected in series with each other and categorised into degrading and binary units. The performance of the BOP system in terms of availability, reliability and mean-time-between failures (MTBF) is obtained and analysed. A sensitivity analysis is also performed to evaluate the effect of fault coverage factor and redundancy design on system performance. The results show that both the

fault coverage factor and redundancy have significant impact on the BOP's reliability, availability and MTBF.

4.1 Introduction

A large number of safety instrumented systems (SISs) are in use within the oil and gas industry for drilling, production, processing and storage purposes (Liu, 2014; Liu and Rausand, 2016). The complexities associated with these systems are amplified when taking into account the myriad of challenges within the offshore environment. The blowout preventer (BOP) is one of the most important SISs in the subsea oil and gas sector which is employed in the event of the failure of the primary well control process.

The main function of a BOP is to seal the well in the event of a blowout (i.e., an uncontrolled flow of liquid and gases during the drilling process) (Holand and Rausand, 1987). The subsea BOPs are one of the most critical SISs among all drilling equipment and, as a result, the downtime associated with removal of the BOP stack is known as one of the costliest losses activities in offshore drilling operations (Zou *et al.*, 2016).

In spite of recent advancements in reliability analysis of SISs, research into the reliability assessment of subsea BOPs is still lacking in some regards. There are gaps in the literature with respect to the incorporation of preventive maintenance (PM) strategies as well as dynamic operating conditions into BOP reliability analysis. To address these gaps, this paper develops a stochastic Petri net (SPN) model to estimate the reliability of subsea BOP systems subject to condition-based maintenance (CBM) with different failure modes. The BOP system is divided into five subsystems which are connected in series with each other and categorised into degrading and binary units. The annular preventers, ram preventers, hydraulic connectors, and choke and kill system are considered as degrading units; whereas the MUX control system is considered as a binary unit. Four different condition states – namely: normal, degraded, critical and failed – are considered for each failure mode. The advanced reliability analysis metrics such as failure criticality index and reliability importance have been obtained, in addition to standard metrics such as the reliability, availability and mean-time

between failures (MTBF). This study, to the best of the author's knowledge, is the first attempt to improve the robustness of the state-of-the-art reliability analysis methods by modelling the operation of the subsea BOP system with multiple degradation states.

The rest of this paper is organised as follows. Section 4.2 provides theoretical background on subsea BOP reliability. Section 4.3 provides an overview on Petri net modelling. In section 4.4, stochastic Petri-net models are developed for different BOP subsystems. Section 4.5 presents the results of the analysis, and section 4.6 concludes the study and proposes directions for future research.

4.2 Reliability analysis of subsea BOPs

The reliability analysis of BOP systems has come into prominence in response to recent incidents that have happened in the oil and gas industry (Liu *et al.*, 2015a). The reliability assessment techniques for subsea BOP systems have evolved considerably since the first study by Holand and Rausand (1987). They employed fault tree analysis (FTA) to estimate the probability of a blowout event using the real data from drilling documents, BOP tests and well equipment failure reports. Some years later, Fowler and Roche, (1993) also used FTA in addition to failure mode and effects analysis (FMEA) to analyse the reliability of a subsea BOP and a hydraulic control system. Zou *et al.*, (2016) applied the reliability block diagram (RBD) technique to analyse the reliability of subsea BOPs. The results were then compared against design requirements. Recently, Shafiee *et al.* (2019b) proposed an integrated FTA and FMEA model to analyse the reliability of subsea BOPs. The study weighted the minimal cut sets derived from the fault trees based on Birnbaum's measure of importance and then used the weights to update Risk Priority Numbers (RPNs) obtained from the use of traditional FMEA.

There are significant drawbacks to using conventional reliability assessment techniques (Animah and Shafiee, 2018). According to Bai *et al.* (2010), complex and dynamic systems are difficult to model using conventional techniques; thus, the numerical analysis of the system's reliability can be extremely arduous. Both the FTA and FMEA techniques only work well for non-repairable systems, and do not possess a time element which is vital a characteristic when analysing complex

subsea systems like the BOP. Furthermore, differentiating between severe failures caused by compound faults and common-cause failures is impossible using the FMEA (Liu *et al.*, 2015a).

Attempts have been made to overcome some of the drawbacks of the conventional reliability assessment techniques (Shafiee *et al.*, 2019a). Advanced reliability techniques such as Bayesian Network (BN), Markov analysis, Monte-Carlo simulation (MCS), Petri Net (PN), and their different variations have been developed and applied to assess the reliability of subsea BOPs (Liu *et al.*, 2017).

BN has recently gained prominence as a robust tool for the reliability analysis of BOP systems (Liu *et al.*, 2015b). This is mainly as a result of its ability to perform fault diagnosis as well as predictive analytics (Cai *et al.*, 2012). Markovian models, such as homogeneous Markov chains or hidden Markov models, have also been used to evaluate the reliability of complex systems such as subsea BOPs. Markov models are very flexible in representing the dynamic behaviour of engineering systems (Boyd, 1998). MCS is also a widely used technique to verify the BOP reliability analysis results obtained with different analytical methods recommended in IEC 61508 (2010). MCS provides a tool to incorporate all practical aspects of system operation (such as failure and repair information) into reliability assessment (Wu *et al.*, 2018). The PN technique, which is used in this study, is a numerical and graphical tool used to model asynchronous, simultaneous, distributed and parallel systems (Sadou and Demmou, 2009). One of its variations, Stochastic Petri Net (SPN) explicitly introduces a time parameter (Cai *et al.*, 2013), making it very suitable for reliability analysis of SISs such as subsea BOPs. In the next subsection, the PN methods are briefly reviewed.

4.3 Petri nets revisited

A Petri Net (PN) is a graphical modelling tool developed by Carl Petri as part of his PhD dissertation (Petri, 1962) to determine the most appropriate method for a defined theory of communication. It is used to model and analyse complex systems which are defined as distributed, stochastic, simultaneous and non-deterministic (Murata, 1989).

A typical PN model comprises of four essential graphical features, namely: places, transitions, arcs and tokens. Places, which represent the state of a system, subsystem or component, are denoted by a hollow circle (Leigh and Dunnett, 2016). Transitions allow the system to change states, making it possible to model the dynamic behaviour of a system and is denoted by a rectangle. Tokens are little solid circles always located within places and represent the current state of the system. Arcs connect places to transitions and vice-versa and are represented by solid arrows (Le and Andrews, 2016). The state of the system being modelled changes when one or more tokens are fired. A token being fired signifies that it has been transferred from one place to another. This event occurs as a result of a transition becoming enabled (Liu *et al.*, 2015a). A transition becomes enabled only when pre-defined requirements are met.

In reliability and safety engineering, the PN technique has been applied towards different subject areas, including: remaining useful life (RUL) prediction (Elmeliani *et al.*, 2013), reliability evaluation (Liu *et al.*, 2017), safety analysis (Leveson and Stolzy, 1987), and maintenance modelling (Rochdi *et al.*, 1999).

The conventional PN, which does not take changes in time into consideration, is defined as a 5-tuple or a finite sequence of five elements (Liu *et al.*, 2013). Those elements are represented as follows:

$$PN = (P, T, F, W, M_0) \quad (4-1)$$

where:

$P = (P_1, P_2, P_3, \dots, P_m)$ represents a finite number of places;

$T = (T_1, T_2, T_3, \dots, T_m)$ represents a finite set of transitions;

$F \subseteq (P \times T) \cup (T \times P)$ represents a set of arcs;

$W : F \rightarrow N - \{\emptyset\}$ represents a weight function; and

$M : F \rightarrow N$ represents the initial marking with $P \cap T = \emptyset, P \cup T \neq \emptyset$

Stochastic Petri net (SPN) is a variation of the conventional PN model which was developed to take the concept of time into account when performing reliability

analysis (Kleyner and Volovoi, 2010). The SPN which forms the basis of our model in this study takes the concept of time into account and helps to analyse the dynamic behaviour of systems. The transitions for SPNs have delay time and this delay can either be deterministic or follow a probability distribution. An SPN is a 6-tuple given by (Liu *et al.*, 2017):

$$SPN = (P, T, F, W, M_0, \lambda) \quad (4-2)$$

where P, T, F, W and M_0 are defined as above, and $\lambda = \{\lambda_1, \lambda_2, \lambda_3, \dots, \lambda_l\}$ represents the set of transition firing rates.

4.4 The proposed SPN model

A SPN model is developed in this section to analyse the degradation performance and reliability of subsea BOPs. Due to the complexity of the system, it is broken into five subsystems. These subsystems include: the ram preventers, annular preventers, choke and kill system, hydraulic connectors and the Multiplex Electro-Hydraulic (MUX) control system. The first four of the aforementioned five subsystems can be described as degrading units, meaning that a measurable amount of time passes from when a fault is detected to when functional failure actually occurs. This time interval is represented by a curve called P-F. The P-F curve is a graph that shows the health of a system over time to identify the interval between potential failure and functional failure (Elusakin *et al.*, 2019). The fifth subsystem, i.e., the MUX control system, is described as a binary unit since a fault in the system immediately causes functional failure. The BOP subsystems are connected in series with each other, meaning that if one of these subsystems fails, the entire system will stop functioning. Redundancies can occur on some of the subsystems such as the annular and ram preventers as well as the MUX control system. The effect of redundancy design on the BOP system performance will be discussed in section 4.5.2.

The SPN technique is employed in this study to model the degradation of different BOP subsystems after which the RBD technique is used to combine results obtained from each individual subsystem and assess the reliability of the whole system. The software tool used to develop the SPN model is TimeNET Version

4. TimeNET was developed at the Technische Universität of Berlin to model SPNs. The ReliaSoft BlockSim 10 software tool was also used to build an RBD model for the entire BOP system and perform the overall reliability analysis. Each component is modelled separately given that they are subject to different failure modes, with different causes having different effects on the overall system.

4.4.1 SPN model for degrading subsystems

The models developed for the four degrading subsystems (i.e., the ram preventers, annular preventers, choke and kill system, and hydraulic connectors) are different but they have a common basis. Each component possesses different failure modes associated with its operation. These failure modes show different ways that the subsystem may fail. Therefore, they occur with different frequencies and their repair times are also different. Four different states are considered to present the health condition of subsystems. These include: normal, degraded, critical and failed. A transition between two states represents the events that take place for degradation to progress from one state to another. In this study, the transitions signify the continued operation of the system as well as the repair process. This means that the condition of each subsystem degrades from the normal state to the degraded state, then to the critical state, and eventually to the functional failure state. The times/delays associated with each transition represent how long it takes for the subsystem to further degrade. In the case of repair, it represents the duration of repair. The movement of the token signifies the change in the asset condition; therefore, the token being situated within the *degraded* place signifies that the asset is in the degraded state.

The SPN models developed for the four degrading subsystems of the annular preventer, choke and kill system, hydraulic connectors and the ram preventers are presented in Figure 4.1 - Figure 4.4, respectively. As can be seen, the models for degrading subsystems begin with a token residing in the normal state, signifying that the subsystem is operating as it normally should. The transition right after the normal state in the prevalent failure mode is enabled and the token is fired.

The failure transition parameters follow Weibull distribution as it most aptly represents condition deterioration in failure-prone systems. The two-parameter Weibull probability distribution function is given by (Nielsen, 2011):

$$f(t|\gamma, \beta) = \gamma/\beta t^{(\gamma-1)} \exp\left\{-\left(\frac{t}{\beta}\right)^\gamma\right\}, \text{ for } \gamma > 0, \text{ and } \beta > 0 \quad (4-3)$$

where γ is the shape parameter and β is the scale parameter. Failure data was sourced from literature (Holand and Awan, 2012), which studied a total of 259 wells and recorded 156 BOP related failures. The maximum likelihood estimator (MLE) technique was applied to estimate the corresponding shape and scale parameters for each subsystem. On the other hand, the repair transitions are assumed to follow exponential distribution. The model input parameters for the four degrading subsystems are given in Table 4.1.

The repair action begins before a failure occurs and after it is determined that the component is in the degraded state; therefore, repair paths are created for each failure mode. This is represented by the token travelling from the degraded state back through the repair transition to the normal state. It is only in the event that the repair action does not take place, that the token continues its movement from the degraded state to the critical state and then to the failed state, signifying functional failure.

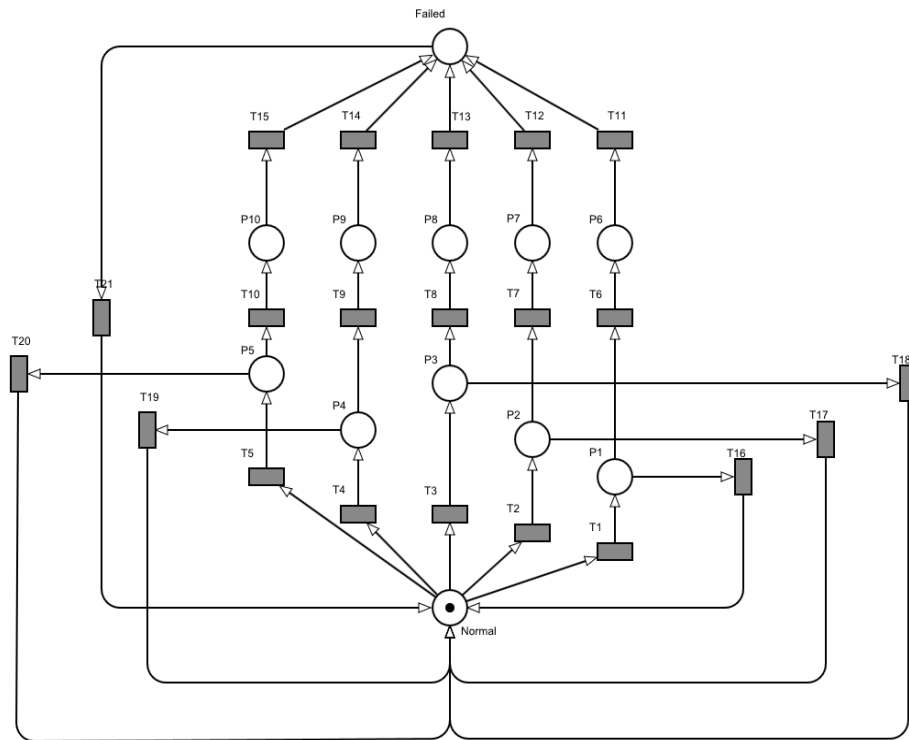


Figure 4.1 Petri net model for the annular preventer system

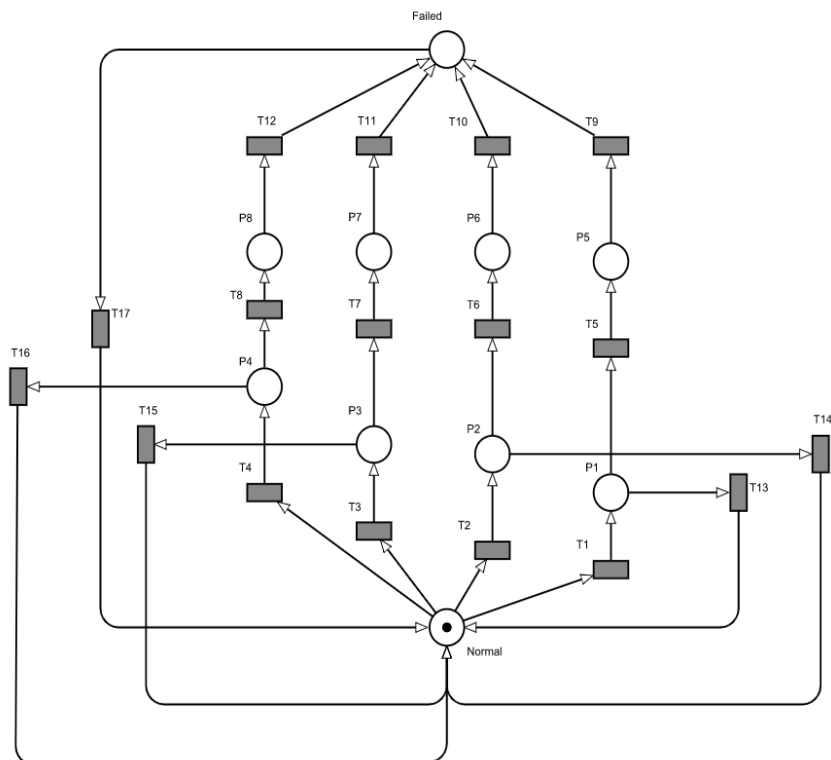


Figure 4.2 Petri net model for choke and kill system

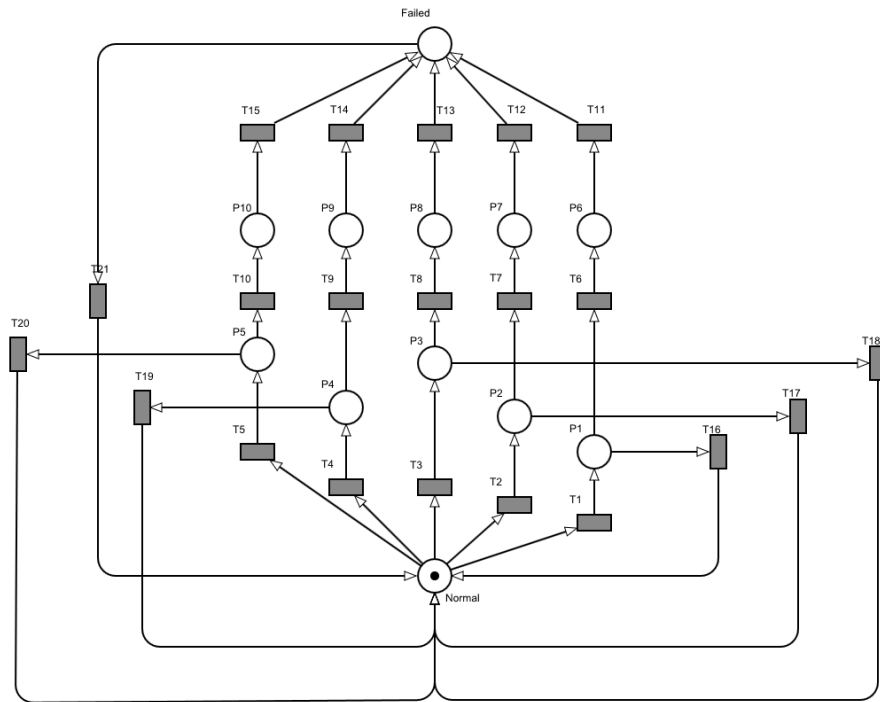


Figure 4.3 Petri net model for hydraulic connectors

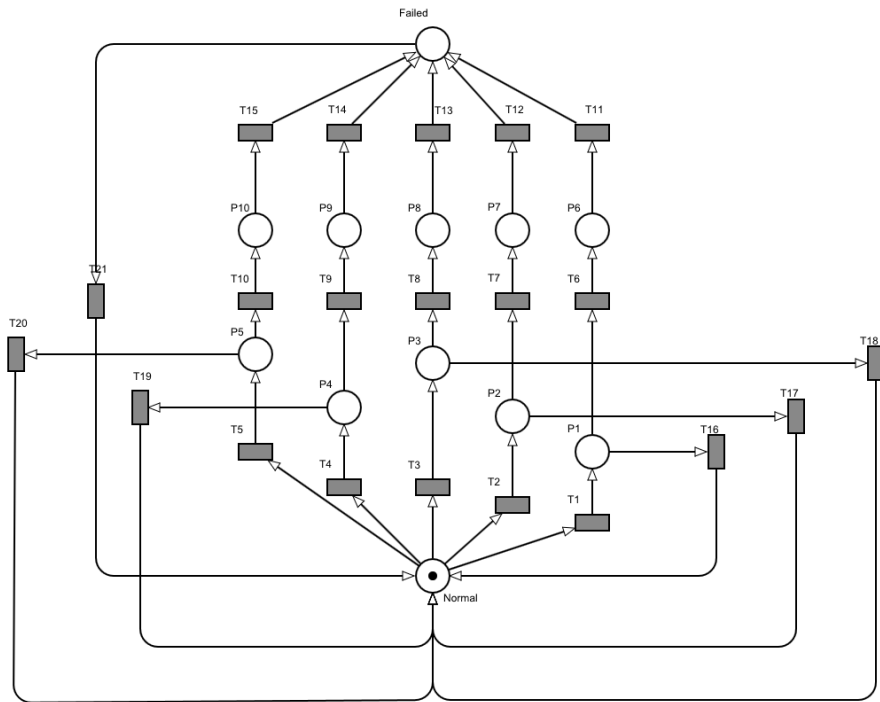


Figure 4.4 Petri net model for ram preventers

Table 4.1 Life data for degrading subsystems

Subsystem	Failure Mode	Degraded Condition (year)	Critical Condition (year)	Functional Failure (year)	Failure Mode Repair time (years)	Subsystem Repair time (years)
Annular preventer	Failure to close	$\gamma = 1.0$ $\beta = 0.61$	$\gamma = 1.0$ $\beta = 0.61$	$\gamma = 1.0$ $\beta = 0.61$	0.0306	0.0112
	Failure to fully open	$\gamma = 0.53$ $\beta = 1.35$	$\gamma = 0.53$ $\beta = 1.35$	$\gamma = 0.53$ $\beta = 1.35$	0.0012	
	Internal control fluid leakage	$\gamma = 1.48$ $\beta = 2.36$	$\gamma = 1.48$ $\beta = 2.36$	$\gamma = 1.48$ $\beta = 2.36$	0.0038	
	Internal leakage through a closed annular	$\gamma = 0.48$ $\beta = 0.60$	$\gamma = 0.48$ $\beta = 0.60$	$\gamma = 0.48$ $\beta = 0.60$	0.0020	
	Other	$\gamma = 1.0$ $\beta = 0.61$	$\gamma = 1.0$ $\beta = 0.61$	$\gamma = 1.0$ $\beta = 0.61$	0.0027	
Ram preventer	External leakage	$\gamma = 1.47$ $\beta = 12.55$	$\gamma = 1.47$ $\beta = 12.55$	$\gamma = 1.47$ $\beta = 12.55$	0.0411	0.0088
	Failure to close	$\gamma = 1.0$ $\beta = 1.61$	$\gamma = 1.0$ $\beta = 1.61$	$\gamma = 1.0$ $\beta = 1.61$	0.0007	
	Failure to fully open	$\gamma = 1.0$ $\beta = 1.61$	$\gamma = 1.0$ $\beta = 1.61$	$\gamma = 1.0$ $\beta = 1.61$	0.0027	
	Internal leakage	$\gamma = 0.43$ $\beta = 0.46$	$\gamma = 0.43$ $\beta = 0.46$	$\gamma = 0.43$ $\beta = 0.46$	0.0072	
	Unknown failure	$\gamma = 1.0$ $\beta = 1.61$	$\gamma = 1.0$ $\beta = 1.61$	$\gamma = 1.0$ $\beta = 1.61$	0.0009	
Choke and kill system	External leakage of BOP attached line	$\gamma = 0.74$ $\beta = 1.83$	$\gamma = 0.74$ $\beta = 1.83$	$\gamma = 0.74$ $\beta = 1.83$	0.0209	0.0134
	Unknown failure	$\gamma = 1.0$ $\beta = 0.33$	$\gamma = 1.0$ $\beta = 0.33$	$\gamma = 1.0$ $\beta = 0.33$	0.0027	
	External leakage on jumper hose line	$\gamma = 1.0$ $\beta = 0.33$	$\gamma = 1.0$ $\beta = 0.33$	$\gamma = 1.0$ $\beta = 0.33$	0.0027	
	External leakage on riser attached line	$\gamma = 0.47$ $\beta = 0.35$	$\gamma = 0.47$ $\beta = 0.35$	$\gamma = 0.47$ $\beta = 0.35$	0.0126	
Hydraulic connectors	External leakage	$\gamma = 0.94$ $\beta = 4.19$	$\gamma = 0.94$ $\beta = 4.19$	$\gamma = 0.94$ $\beta = 4.19$	0.0096	0.0091
	Failure to lock	$\gamma = 1.0$ $\beta = 0.65$	$\gamma = 1.0$ $\beta = 0.65$	$\gamma = 1.0$ $\beta = 0.65$	0.0192	
	Failure to unlock	$\gamma = 1.0$	$\gamma = 1.0$	$\gamma = 1.0$	0.0109	

	$\beta = 0.65$	$\beta = 0.65$	$\beta = 0.65$	
Spurious unlock	$\gamma = 1.0$ $\beta = 0.65$	$\gamma = 1.0$ $\beta = 0.65$	$\gamma = 1.0$ $\beta = 0.65$	0.0027
Unknown failure	$\gamma = 1.46$ $\beta = 2.57$	$\gamma = 1.46$ $\beta = 2.57$	$\gamma = 1.46$ $\beta = 2.57$	0.0056

4.4.2 SPN for binary systems

The SPN model for binary systems (i.e., the MUX control subsystem) begins with the token residing in the normal state, indicating that it is operating normally. Since this is a binary system, only two states are involved: normal and failed. The SPN model developed for the MUX control subsystem is presented in Figure 4.5.

There are also six exponential transitions between both states, with each transition representing a different mode by which the control system may fail. Upon failure, which is signified by the token being in the failed state, the repair transition is activated and the token is fired, taking the control system back into the normal state. The transitions for the MUX control subsystem are exponential transitions as there is no requirement to model degradation.

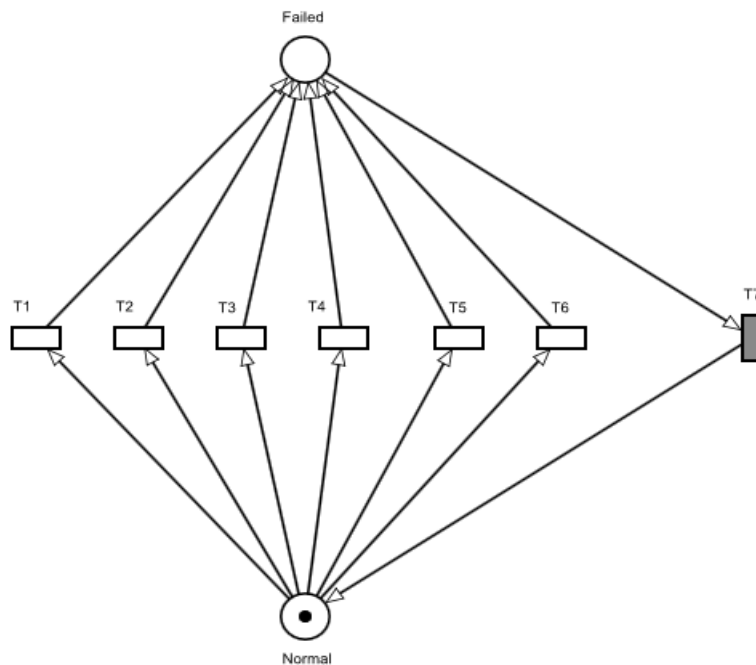


Figure 4.5 Petri net model for MUX control system

The model input parameters for the MUX control subsystem are obtained from Holand and Awan (2012) and are given in Table 4.2.

Table 4.2 Model input parameters for the MUX control subsystem

Subsystem	Failure Mode	MTTF (years)	Failure Mode Repair time (years)	Subsystem Repair Time (years)
MUX Control System	Loss of all functions: both pods	9.85×10^{-3}	2.05×10^{-6}	0.0074
	Loss of all functions: one pod	8.21×10^{-4}	1.6×10^{-5}	
	Loss of one function: both pods	2.48×10^{-3}	1.71×10^{-6}	
	Loss of several functions: one pod	9.85×10^{-3}	0.61×10^{-6}	
	Other	5.22×10^{-4}	1.15×10^{-5}	
	Unknown failure	1.23×10^{-3}	3.42×10^{-6}	

The reliability data obtained from the SPN simulation of each BOP subsystem is then used as input data for reliability modelling of the entire BOP system using the RBD technique.

4.5 Results and analysis

4.5.1 Reliability

The reliability of a system is defined as the probability that it will perform its intended function(s) for a specified period of time under the specified conditions (Zengkai et al., 2013). The subsystems of the BOP system are all connected in series. Therefore, the failure of one subsystem will invariably lead to the failure of the entire BOP system. The reliability of the BOP system is calculated by:

$$R(t) = \prod_{i=1}^n R_i(t) \quad (4-4)$$

where n represents the number of subsystems and $R_i(t)$ represents the reliability of the subsystem i in the system.

The transient reliability plots for the five BOP subsystems are depicted in Figure 4.6. As can be seen, the reliability of the MUX control subsystem decreases more sharply than the reliability of other subsystems, meaning that it is the least reliable subsystem of the BOP. The reliability plots of the annular and ram preventer systems follow very similar trajectories, gradually decreasing until they reach zero after about 50 years. The hydraulic connector subsystem is seen to have slightly higher reliability over time; however, its reliability reaches zero at the same time as the annular and ram preventers. Lastly, the choke and kill system is shown to have the highest reliability over time by a significant margin.

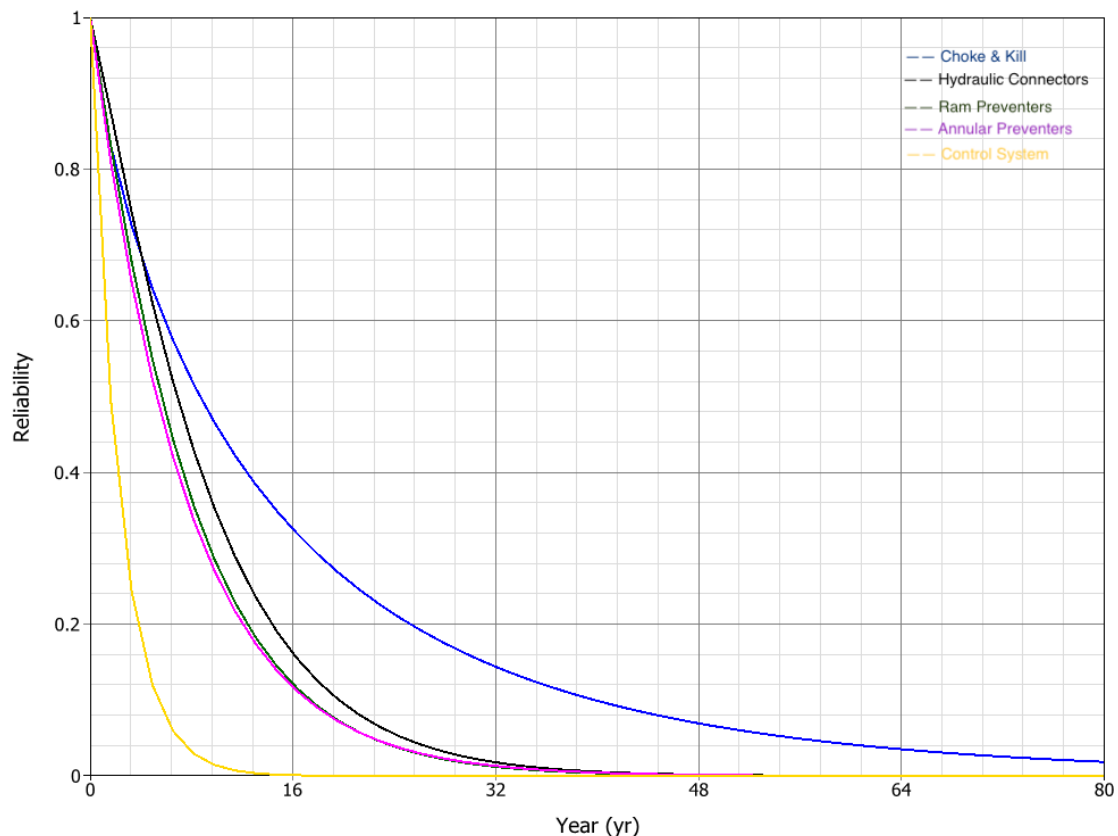


Figure 4.6 Reliability of five main subsystems

The reliability of the entire BOP system is plotted in Figure 4.7. The graph shows that the BOP reliability decreases rapidly during the early years of operation and then reduces gradually until it reaches zero. This means that the probability that the system will successfully perform its required functions eventually drops to zero.

The availability of the BOP system over the first five years is also shown in Figure 4.8. It is seen that the availability of the system drops significantly during the first year of operation. Availability values are reliant on failure rates as well as repair times of the BOP subsystems.

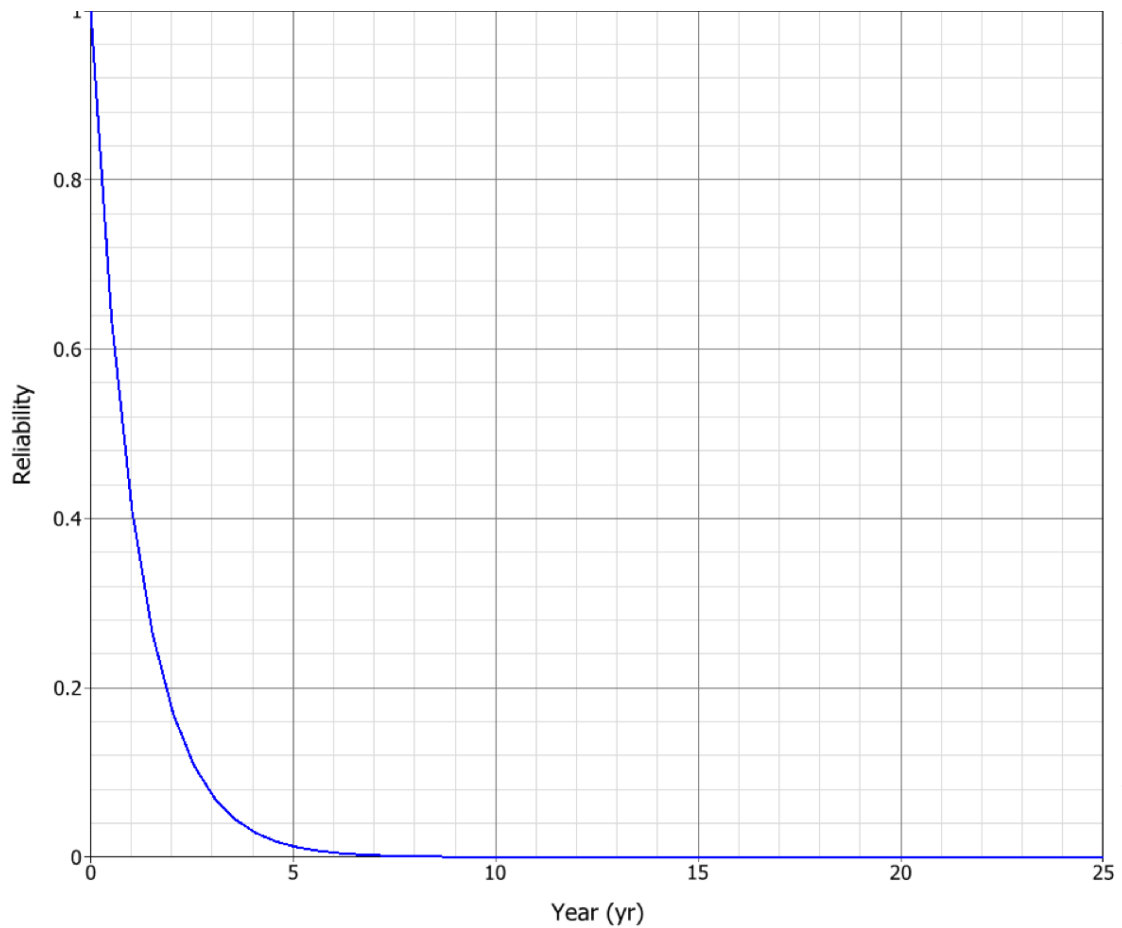


Figure 4.7 Reliability of the entire BOP system

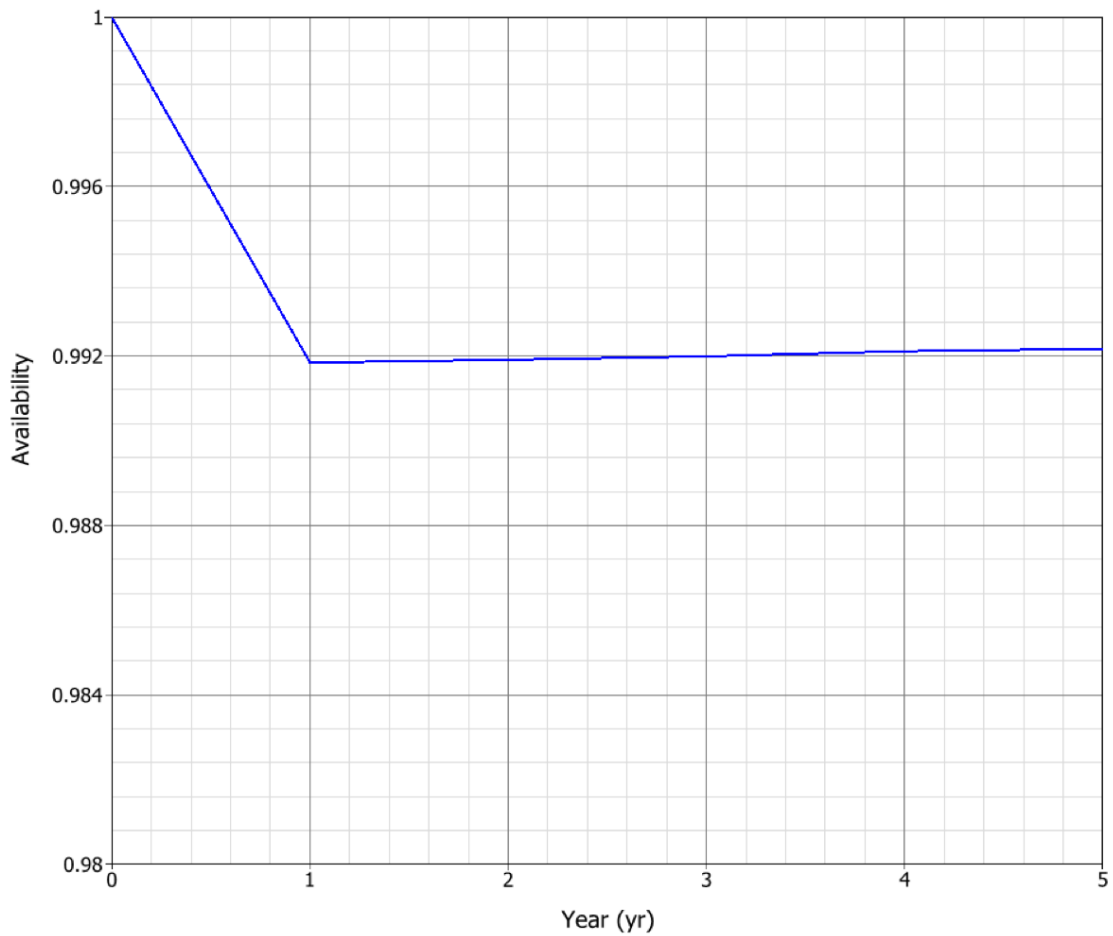


Figure 4.8 Transient availability of the entire BOP system

In order to determine the effects of the reliability of each examined subsystem on the overall BOP system reliability, the reliability importance (RI) of each subsystem is plotted over time. RI is used as a means of determining the relative reliability significance of each subsystem with respect to the overall system reliability. The formula to obtain reliability importance is given by:

$$I_R(t) = \frac{\partial R_s(t)}{\partial R_i(t)} \quad (4-5)$$

where $R_s(t)$ and $R_i(t)$ denote the overall system reliability and the subsystem reliability at a given time t , respectively. Since the BOP is considered as a series system, the least reliable component will have the highest impact on the reliability of the system and hence the highest reliability importance. From Figure 4.9, the MUX control system can be seen to have the highest reliability importance. This

is in agreement with the study performed by Holand and Awan (2012), showing the control subsystem to be the most critical subsystem within the BOP system. This also indicates that the control system requires the most attention with regards to inspection and maintenance.

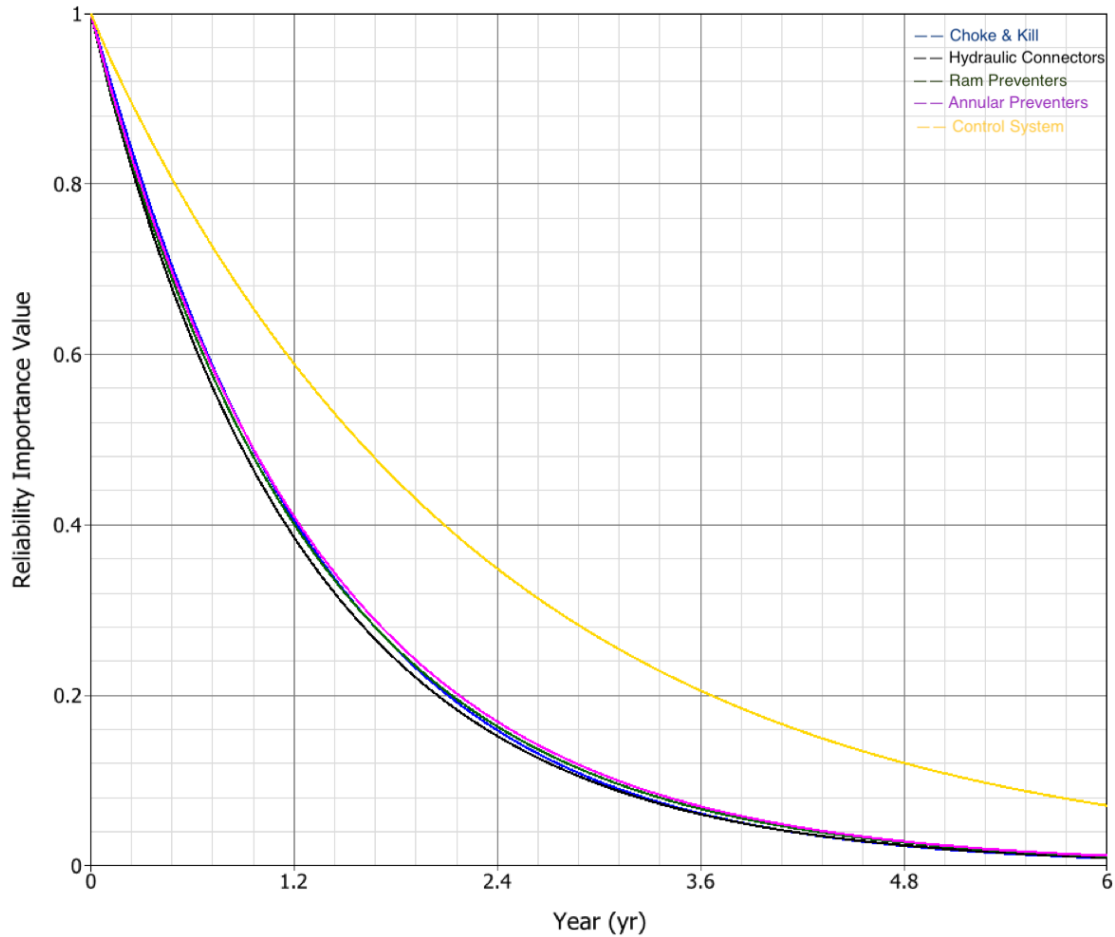


Figure 4.9 Reliability importance of five main BOP subsystems

The failure criticality index (FCI), which identifies the contribution of each subsystem to the overall BOP system failure, is also determined. FCI can be calculated by the following equation:

$$FCI_i = \frac{\text{Number of failures caused by subsystem } i \text{ in } (0, t)}{\text{Number of BOP system failures in } (0, t)} \quad (4-6)$$

The FCI plot in Figure 4.10 shows that the MUX control system has the highest FCI by a considerable margin with a value of 49.7%, followed by the annular preventer at 15.5%, ram preventer at 14.3%, hydraulic connectors at 12.1% and

the choke and kill system at 8.4%. This therefore means the MUX control system is responsible for nearly half of the BOP failures.

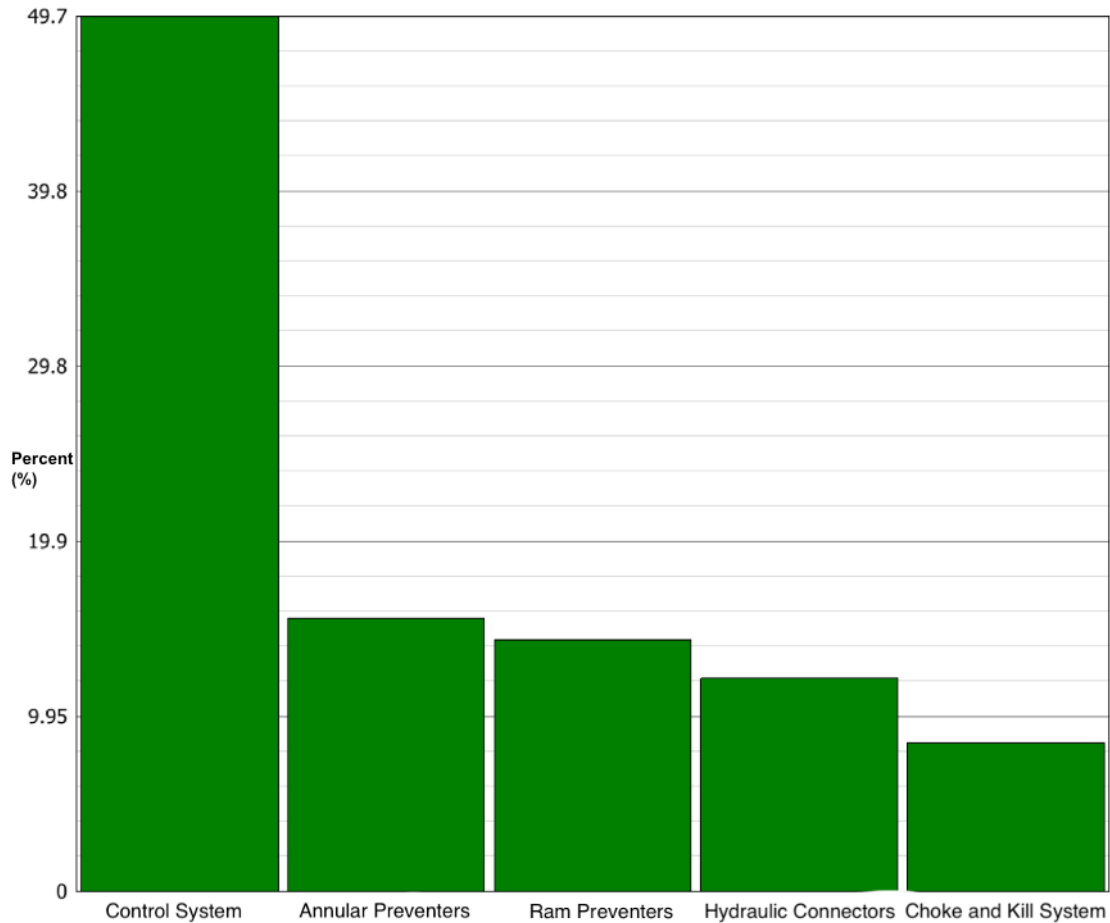


Figure 4.10 Failure criticality index for five main BOP subsystems

The mean time between failure (MTBF) for the entire system is also obtained. The MTBF is an important reliability metric which is calculated by dividing the total amount of time the system should be in operation by the number of times maintenance actions occurred. Therefore,

$$MTBF = \frac{T}{M} \quad (4-7)$$

The MTBF of the BOP system is calculated as 1.14 years.

4.5.2 Sensitivity analysis

A sensitivity analysis has been performed to evaluate the effect of key decisions (such as changing the fault coverage factor and adding redundancy) on the BOP system performance. The fault coverage factor is a key metric in assessing the effectiveness of condition monitoring (CM) solutions (Animah *et al.*, 2018). This factor refers to the percentage of faults that can be detected during the monitoring of any engineered system. The fault coverage can range from 0% to 95–100%, depending on the chosen CM technique for every given fault.

The effects of the fault coverage factor on the system availability, failure criticality index and MTBF are analysed. Figure 4.11 shows the effect of different fault coverage factors on BOP availability. As can be seen, the availability of the BOP system decreases as the fault coverage factor drops. The lower the coverage factor, the less likely it is for failure to be detected and the lower the system availability.

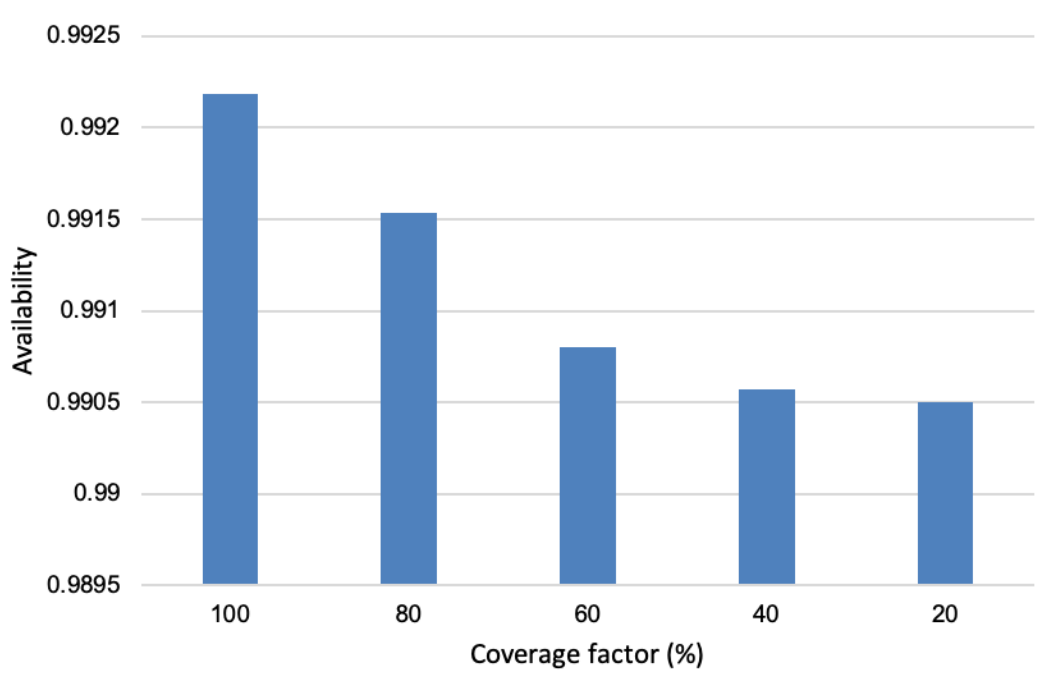


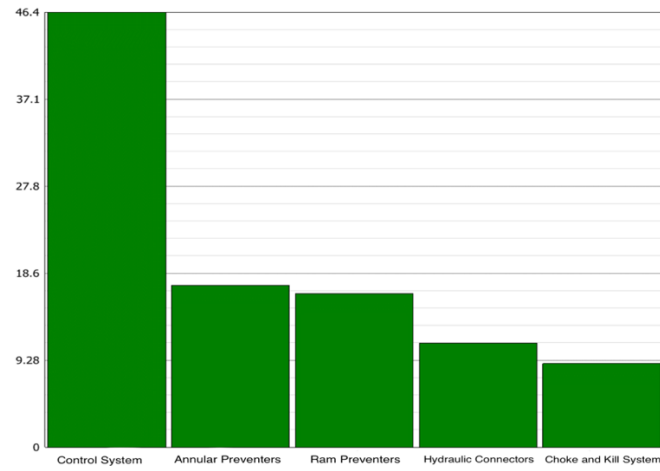
Figure 4.11 Effect of fault coverage factor on BOP system availability

Figure 4.12 shows the effects of different fault coverage factors at 80%, 60%, 40% and 20% on the system failure criticality index (FCI). As can be seen, a

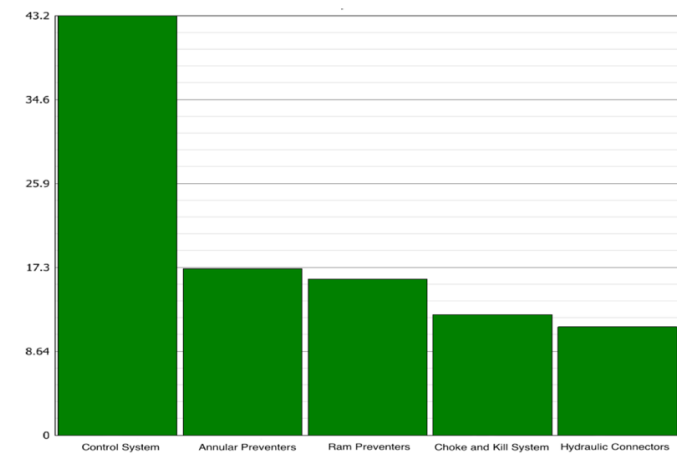
decrease in fault coverage factor results in corresponding decrease in FCI for the MUX control system. The fault coverage factor, however, does not seem to affect the order of subsystems in the FCI plots as there is no discernible pattern in subsystem order as the fault coverage factor decreases.

The effect of variation in fault coverage factor on the MTBF has also been investigated. The results of this analysis are given in Table 4.3. The MTBF of the BOP system is seen to decrease when the coverage factor reduces. This therefore means that the amount of time that the system remains in operation reduces as fault detection becomes less effective.

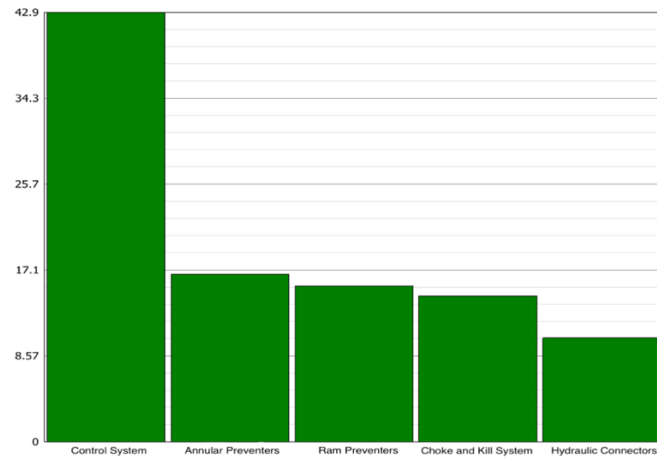
A new redundant BOP configuration by adding a second MUX control system to the conventional BOP is introduced. The MUX control system is chosen because it is the most critical subsystem. The effect of redundancy on BOP system availability is investigated and the results show that the BOP system availability increased by 0.03% from 0.9922 to 0.9925. The effect of redundancy on the MTBF of the BOP system has also been investigated with the results showing an increase of 4.4% in MTBF from 1.14 years to 1.19 years. The increases in both MTBF and availability reflect the benefit of redundancy to subsea BOP systems.



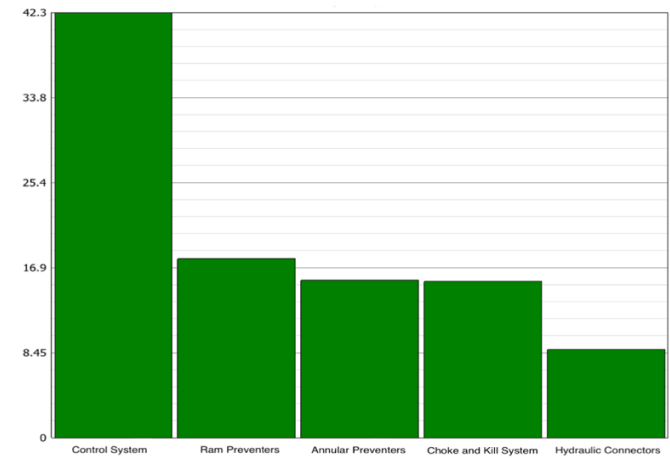
(a)



(b)



(c)



(d)

Figure 4.12 The effects of (a) 80% coverage factor (b) 60% coverage factor (c) 40% coverage factor (d) 20% coverage factor on the system failure criticality index (FCI)

Table 4.3 Effect of coverage factor on MTBF

Coverage Factor (%)	Mean Time Between Failures (Years)
100	1.14
80	1.06
60	1.00
40	0.99
20	0.98

4.6 Conclusion and future works

This paper presented an advanced reliability analysis technique using stochastic petri nets (SPN) and reliability-block diagram (RBD) for subsea blowout preventer (BOP) systems while incorporating the degradation and condition monitoring (CM) information. The subsea BOP was divided into five subsystems (including annular preventers, ram preventers, hydraulic connectors, choke and kill system, and MUX control system) which are connected in series with each other. The reliability, availability and mean time between failures (MTBF) of the BOP system were estimated. The control system was concluded as being the least reliable subsystem and this was confirmed by the control system having the highest reliability importance by a significant margin as well as being responsible for nearly half of the total system failures. The MTBF of the entire BOP system was determined to be 1.14 years. A sensitivity analysis was also performed to evaluate the effect of improving fault coverage as well as adding redundancy (in the form of an additional MUX control system) on the BOP system performance. The results showed that both the fault coverage and redundancy had significant impact on the system availability and MTBF but little discernible effect on the failure criticality index (FCI). As coverage factor decreased, so did the system availability and MTBF emphasising the importance of accurate detection of faults in subsea BOP operation. Adding a second MUX control system also led to increase in system availability and MTBF.

There is potential for future research in the area of reliability analysis of subsea safety instrumented systems. For this research, we only studied the reliability of the subsea BOP system when considering CM and system degradation. A

promising avenue for future research can be the adaptation of the methodology applied in this research study for other subsea assets. Another promising avenue for further research can be on the performance of reliability analysis of subsea safety instrumented systems based on different forms of degradation. Research on the use of coloured Petri nets (CPNs) for reliability analysis of complex subsea systems is another opportunity which can be explored in the future (see Noori and Waag (2019)).

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5 DEVELOPMENT OF A DYNAMIC BAYESIAN NETWORK MODEL FOR RELIABILITY AND FAULT DIAGNOSIS OF OFFSHORE WIND TURBINE GEARBOX

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Statement of contribution:

Tobiloba Elusakin was responsible for study conceptualisation, methodology, software, validation, formal analysis, investigation, data curation, writing - original draft, review and editing, visualisation and project administration. Dr Mahmoud Shafiee was responsible for formal analysis, investigation, review and editing, visualisation and supervision. Professor Nigel Simms was responsible for review and editing, and project supervision. Tosin Adedipe was responsible for review and editing.

Abstract

For offshore wind turbines, the ever-increasing global energy demand has necessitated a gradual move further offshore and into deeper waters to take full advantage of more available space and considerably higher wind speeds. The wind turbine gearbox, due to its complexity and connectivity to other drivetrain components, is one of the most critical and expensive systems to maintain in the offshore wind turbine. Despite recent studies about reliability assessments of offshore wind turbines, the gearbox has received little attention. In particular, there are gaps in literature with respect to the reliability analysis and fault diagnosis of the offshore wind turbine gearbox. This study carries out a detailed advanced reliability analysis and fault diagnosis of the gearbox system and its subassemblies using a dynamic Bayesian network (DBN) framework with incorporating component degradation and condition-based maintenance (CBM). For the purpose of this modelling, the gearbox system is broken down into five degradable subassemblies connected to each other in series. The reliability, availability and mean time between failures (MTBF) have been determined along with reliability importance and failure criticality index (FCI) for each subassembly. Fault diagnosis has also been performed, identifying the loss of function in the

bearing subassembly as the most likely root cause of gearbox failure. A sensitivity analysis is also conducted to determine the effects of fault coverage factor on reliability, availability, MTBF and the expected number of failures, as well as the effect of redundancy on MTBF and expected number of failures.

Keywords: Offshore wind turbine, gearbox, reliability, mean time between failure, fault diagnosis, dynamic Bayesian network (DBN).

5.1 Introduction

The offshore wind energy industry has experienced an exponential growth over the past decade. In 2019 alone, Europe saw an increase in installed offshore wind energy gross capacity of 3,627MW – representing approximately 24% of the overall installed capacity (Wind Europe, 2020). To accommodate growing energy demand, offshore wind is also gradually moving further offshore and into deeper waters due to availability of more space and higher wind speeds (Kang *et al.*, 2017). As a result of the erratic weather conditions and the harsh offshore environment, offshore wind turbines are subject to higher failure rates and considerable challenges to their repair processes (Li *et al.*, 2019). The transition to deeper waters has also necessitated the design, fabrication and installation of larger capacity wind turbines to take advantage of higher wind speeds. However, the increase in wind speeds leads to higher loading on the wind turbines' subsystems (such as the drivetrain) which in turn contributes to accelerated degradation (Romero *et al.*, 2018).

The gearbox system, which is part of the drivetrain, is one of the most important assemblies within a wind turbine system. Its main function is to transmit power from the rotor to the generator by increasing the low input rotational speed from the rotor at high torque to a high output speed for the electric generator at low torque (Bhardwaj *et al.*, 2019b). As a result of the variations in wind speed offshore, the gearbox is subject to oscillating loads, making it one of the most vulnerable and least reliable wind turbine subsystems, as well as being the biggest contributor to overall wind turbine failure downtime (Li *et al.*, 2017). This makes the research into OWT gearbox reliability vital for the operation of the entire wind turbine system.

The gearbox is a complex mechanical asset comprising of multiple components which are repairable and degrade with use. It is classified as a wind turbine assembly and is categorised under the drive train subsystem. It can further be broken down into subassemblies such as gears, bearings, lubrication system, housing and shafts. A standard wind turbine gearbox including its key elements is shown in Figure 5.1.

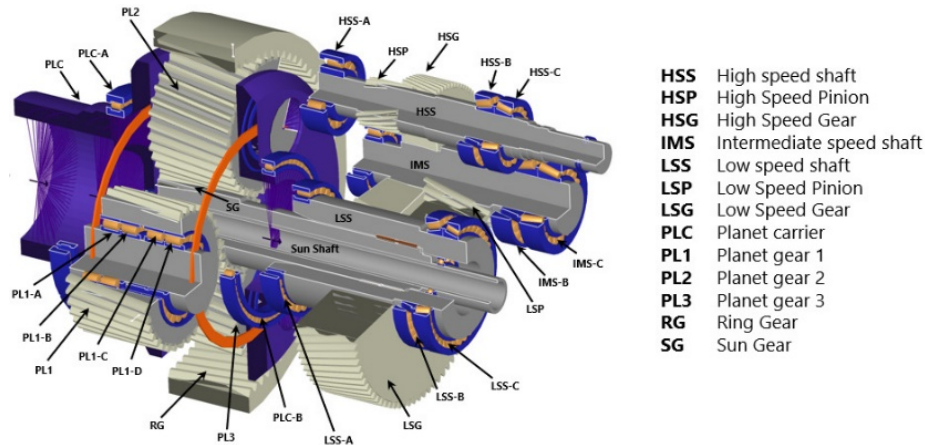


Figure 5.1 Typical modern design of a wind turbine gearbox (Onyx Insight, 2019)

In offshore wind turbine operations, gearboxes face various issues which present challenges in their design, fabrication, installation, and operation and maintenance (O&M). These issues include changing weather conditions, temperature, wind speed, wind shear and loading. These factors make it inappropriate to apply reliability and performance requirements of onshore wind turbines and their components to their offshore counterparts (Hameed *et al.*, 2011). In order to account for the heightened harshness of the offshore environment, the reliability of the offshore wind turbine (OWT) gearboxes require special attention because any functional failure results in prolonged periods of wind turbine shutdown and major maintenance works, which consequently lead to considerable losses in terms of both power and finances.

Despite recent reliability assessments of offshore wind turbines (see, e.g. Klakegg, 2012; Guo *et al.*, 2015; Luengo and Kolios, 2015; Leigh and Dunnett, 2016; Zhang *et al.*, 2016; Kang *et al.*, 2019, Li *et al.*, 2020), the assessment of the gearbox reliability still requires further research. There are gaps in the

literature with regard to the reliability analysis of the OWT gearbox as a multi-component system while taking into account degradation, repairability and the condition-based maintenance (CBM) strategy. Previous studies are also severely lacking with respect to the performance of fault diagnosis on the OWT gearbox (i.e., determining which subassemblies have failed and how much each subassembly contributes to the overall gearbox failure). To address these gaps, this study develops a dynamic BN model to perform reliability analysis and fault diagnosis of the OWT gearbox taking into account degradation and condition-based maintenance. The BN technique is applied in this study as a reliability analysis tool because it provides a number of advantages. It is able to perform both prognostic (forward) and diagnostic (backward) analysis of a system; accommodate both discrete and continuous models of time; and support decision-making by incorporating decision and utility nodes. Dynamic Bayesian Networks (DBNs) are then able to extend these advantages by incorporating the temporal nature of the system being analysed.

The subassemblies of the gearbox are connected in series signifying that the failure of one subassembly can lead to system breakdown. The operation of each subassembly is broken down into four different condition phases, represented by different time slices. The lifetime distributions of each subassembly as well as their failure modes are prerequisites for performing reliability analysis of the gearbox system by using BNs. The reliability, mean time between failures (MTBF) and reliability importance of each subassembly are obtained. For this study, the R80 gearbox configuration with nominal power of 2MW has been considered. This configuration contains a combination of one planetary stage and two parallel stages.

The rest of the paper is organised as follows. Section 5.2 reviews and discusses the previous research on offshore wind turbine gearbox reliability. Section 5.3 revisits the Bayesian network technique. Section 5.4 presents the dynamic Bayesian network modelling performed for the OWT gearbox. Section 5.5 discusses the results obtained and analyses performed, and section 5.6 concludes the study.

5.2 Reliability analysis of offshore wind turbine gearboxes

The reliability analysis of offshore wind turbines has been the focus of many studies in recent years (see Nielsen and Sørensen, 2014; Guo *et al.*, 2015; Le and Andrews, 2016; Leigh and Dunnett, 2016; Zhang *et al.*, 2016; Li *et al.*, 2018; Kang *et al.*, 2019). However, the reliability of the gearbox itself has not been focused on. The reliability analysis of offshore wind turbines and their components is a relatively new concept, having only gained prominence within the last two decades. Dinmohammadi and Shafiee (2013) applied a fuzzy failure mode and effect analysis (FMEA) towards performing risk assessment of offshore wind turbines and its components/subsystems. This was done in order to improve the efficiency of the traditional FMEA technique and overcome its drawbacks, e.g., the unreliability of SCADA data and the challenges involved in the evaluation of risk factors by experts. In this study, the gearbox was determined to be second and third most critical wind turbine subsystem in the traditional and fuzzy FMEA analyses, respectively. In Shafiee and Dinmohammadi (2014), the reliability of both onshore and offshore WTs were analysed and compared using an extended FMEA technique which takes into account both risk priority number (RPN) and cost priority number (CPN) measures. This study also ranked the gearbox as second most critical in both types of wind turbines. Guo *et al.* (2015) performed a reliability analysis of a floating offshore wind turbine (FOWT) by combining both reliability block diagram (RBD) and fault tree analysis (FTA) techniques. The study concluded that the yaw system, gearbox, cooling system and mooring system should be given the most attention. Kang *et al.* (2019) applied the FTA to analyse the reliability of a semi-submersible FOWT and its subsystems in qualitative and quantitative ways. The gearbox was analysed in this study and materials degradation was found to be its most prevalent failure mode.

With respect to gearboxes specifically, a number of studies have been conducted. In Yang and Jiang (2011), the reliability of an offshore wind turbine gearbox was analysed as part of an effort to describe how wind farm SCADA systems contribute to the development of a reliability centred maintenance (RCM) strategy. Bhardwaj *et al.* (2019) performed a component level reliability prediction by using the FMEA technique to determine failure causes, and then applied a

stepwise reliability prediction method to estimate the overall gearbox failure rate. In Li *et al.*, (2019), the non-homogenous continuous time Markov process was applied to develop optimal maintenance policies for an offshore wind turbine, considering the gearbox to be a multi-state system.

A number of other studies, while not addressing reliability analysis, have focused on WT gearbox failures on a component level. In Zhao *et al.* (2012) a method was proposed for the prediction of wind turbine gearbox failures based on least square support vector machines (LSSVM). Sheng (2014) conducted a study in which 320 gearbox damage records were surveyed with the aim of identifying top failure modes and root causes. Both these studies identified the bearings as the most frequent reason for gearbox failure with the latter finding that 70% of gearboxes were attributable to the bearing alone.

The majority of reliability analysis studies performed on WT gearboxes have applied conventional analysis techniques which fail to take into account the dynamic, non-binary and multi-component nature of a mechanical assembly such as the gearbox. Conventional reliability analysis techniques are known to possess significant downsides (Animah and Shafiee, 2018; Shafiee *et al.*, 2020). The traditional FMEA and FTA techniques do not take into account the degradable nature of assets over time and are only suitable for non-repairable systems (Elusakin and Shafiee, 2020). Furthermore, in FMEA, the risk priority number (RPN) alone does not provide detailed enough information on the rankings of components and subsystems in a complex system such as the offshore wind turbine (Shafiee and Dinmohammadi, 2014).

To overcome these drawbacks, advanced reliability analysis techniques have been adopted in a number of studies. In Lazakis and Kougioumtzoglou (2017), Bayesian Belief Network (BBN) was applied with FMECA and HAZID to rank OWT components based on their criticality. The Petri net (PN) technique has also been applied by Le and Andrews (2016) to model the degradation process, inspection and maintenance of offshore wind turbines. This study applied an extension of the PN technique, stochastic Petri net (SPN) in order to capture the dynamic and stochastic nature of offshore wind turbine operation. The

components of the OWT were modelled to degrade into several discrete states based on Weibull distributed failure rates.

Table 5.1 presents a summary of key literature which have analysed the reliability of offshore wind turbines and their components, highlighting the particular asset focused on and the method applied for reliability analysis.

Table 5.1 Studies showing reliability analysis of OWT and components

Reference	Component/System	Technique/Method	Principal Focus
Seebregts <i>et al.</i> , (1995)	Wind Turbine System	FMECA, Event Tree Analysis (ETA) and FTA	The system reliability, availability and damage frequencies
Haigui <i>et al.</i> , (2008)	Offshore Wind Turbine (OWT) Tripod Foundation	Numerical method with support vector machine (SVM)	A simple simulation method based on support vector machine (SVM) was proposed to achieve a more efficient reliability assessment.
Dong <i>et al.</i> , (2010)	Fixed-jacket OWT	FORM	In the present paper the effect of inspection on the reliability of welded tubular joints in jacket-type offshore wind turbine structures was quantified.
Thöns <i>et al.</i> , (2010)	OWT Tripod Support Structures	Response Surface Method	Reliability analysis for a tripod support structure of a Multibrid M5000 wind turbine was performed.
Sultania & Manuel, (2011)	Spar-supported FOWT	FORM	50-year response values for a model of a 5-MW spar buoy-supported floating offshore wind turbine were predicted.
Yang & Jiang, (2011)	OWT System	FMECA	The reliability of the OWT was estimated based on supervisory control and data acquisition (SCADA) data
Dong <i>et al.</i> , (2012)	OWT Jacket Support Structure	Fatigue Reliability Analysis	In this paper prediction of fatigue reliability of welded multi-planar tubular joints of the support structure of a fixed jacket offshore wind turbine is performed. The

			effects of inspection and repair taking and not taking corrosion into account are also determined.
Dinmohammadi & Shafiee (2013)	Offshore Wind Turbine System	Fuzzy-FMEA	A fuzzy inference approach is considered to represent the assessment information using linguistic terms. Then, by using the weight vector of three risk factors, a grey theory analysis is proposed to rank the failure modes
Dong <i>et al.</i> (2014)	OWT tower	Unit-load method	The reliability model of the OWT tower under reliability rigidity decay and the reliability index of OWT tower under fatigue loading was determined.
Shafiee & Dinmohammadi (2014)	Offshore Wind Turbine System	FMEA	A new tool for risk and failure analysis was developed by extending traditional FMEA to include economic considerations. The tool was used to conduct reliability analysis for an OWT.
Yoon <i>et al.</i> (2014)	OWT Monopile	Response Surface Method (RSM)	This paper investigates the best combinations of the RSM techniques with a reliability analysis of monopile for an offshore wind foundation.
Guo <i>et al.</i> (2015)	FOWT System	Reliability Block Diagram (RBD) and FTA	The FOWT components which required the most attention were highlighted.
Kim <i>et al.</i> (2015)	Jacket-type OWT Support Structure	FORM	The reliability index of the support structure of a 5MW OWT was determined using first order reliability method (FORM).
Yeter <i>et al.</i> (2015)	OWT Jacket Support Structure	Fatigue Reliability Analysis	The effect of inspection on welded tubular joints in jacket type offshore wind turbine structures was quantified along with the effects of corrosion.

Yoon <i>et al.</i> (2015)	Offshore Wind Turbine (OWT) Monopile Foundation	First Order Reliability Method (FORM) with Response Surface Method	The reliability indices and probabilities of failure were determined for each critical failure mode.
Yi <i>et al.</i> (2016)	Bottom-fixed OWT System	FORM	Numerical analysis of an NREL 5 MW wind turbine supported by monopile, tripod and jacket substructures was performed to determine the effect of soil properties on the reliability index.
Zhang <i>et al.</i> (2016)	FOWT System	Fault Tree Analysis (FTA)	Failure rate and MTTF of the FOWT were determined.
Kang <i>et al.</i> (2017)	FOWT System	Correlation FMEA	The failure modes with the highest RPN values were calculated.
Li <i>et al.</i> (2017)	Offshore Wind Turbine Gearbox	Markov Models	The reliability, availability, maintenance times and downtime for corrective and preventive maintenance models of the OWT were determined
Fazeres-Ferradosa <i>et al.</i> (2018)	Spar-supported FOWT	2-D and 3-D Inverse FORM	The dynamic behaviour of the coupled platform-turbine system was studied, and critical combinations of wind speed and wave height identified.
Hu <i>et al.</i> (2018)	OWT Foundation	Bayesian Network	This paper presented a detailed procedure to generate the joint distribution of mean wind speed, significant wave height, and peak wave period, which was implemented in reliability analysis of offshore wind turbines.
Kolios & Wang (2018)	OWT Monopiles	FORM	FORM is used to calculate the fatigue reliability index of an OWT monopile
Bhardwaj <i>et al.</i> (2019a)	OWT Gearbox	Failure Mode, Effect and Criticality Analysis (FMECA)	The failure rate for OWT gearbox was determined with main failure modes, causes and reliability

			influencing factors (RIFs) for each subassembly being determined
Bhardwaj <i>et al.</i> (2019b)	OWT Gearbox Bearings	FMECA	The main reliability influencing factors (RIFs) for failure causes were determined along with the total failure rate of the OWT gearbox bearing.
Horn & Leira (2019)	Offshore Wind Turbine (OWT) Monopile Foundation	FORM	The reliability index and availability of the FOWT foundation was determined to reduce the probability of failure and increase operational lifetime.
Kang <i>et al.</i> (2019)	FOWT System	FTA	The overall failure rate for the entire FOWT system was determined along with prevalent causes of component malfunction.
Liu <i>et al.</i> (2019)	FOWT Blades	Numerical method	The failure probabilities of the failure modes blade root overload, blade root fatigue and excessive displacement of the blade tip are analysed.
Li and Guedes Soares (2020)	FOWT Support Structures	Hierarchical Bayesian Network (HBN)	In the failure propagation layer, failure probability, reliability, failure rate, mean time to failure with respect to service time are estimated. The primary influencers of support structure failure are also outlined.
Li <i>et al.</i> (2020)	Floating Offshore Wind Turbine (FOWT) System	Bayesian Network (BN)	The failure probability, reliability, failure rate and mean time to failure (MTTF) at certain times were determined.
Li <i>et al.</i> (2020)	Offshore Wind Turbines System	Fault Tree Analysis	A reliability model which takes component swapping into account was proposed to obtain a robust reliability assessment of redundant systems in OWTs. The reliability importance indices (marginal and joint) of critical components are calculated.

Shittu <i>et al.</i> (2020).	OWT Support Structure	FORM and MCS	The reliability index of an OWT support structure was estimated
Velarde <i>et al.</i> (2020)	OWT Monopile	Fatigue Reliability Analysis	Fatigue reliability analysis of a wave sensitive, large monopile supporting a 10 MW offshore wind turbine is demonstrated and a minimum fatigue design factor was recommended.

From Table 5.1, it can be seen that the OWT support structures which include the foundation and tower have been the most popular wind turbine component for reliability analysis, followed by the entire OWT system and then the OWT gearbox. This is unsurprising due to the highly critical nature of the OWT structure and the high cost of O&M associated with it. The most applied reliability analysis technique was found to be first order reliability method (FORM), followed by failure mode and effect analysis (FMEA), fault tree analysis (FTA) and response surface method (RSM).

5.3 Bayesian networks revisited

Bayesian networks (BN) provide a method through which probabilistic connections between variables can be modelled. Developed in the 1980s, the technique is rooted in statistics and provides a simplistic way to solve complex decision-making problems (Lazakis and Kougoumtzoglou, 2019). The BN consists of nodes which represent random variables, arcs which link nodes in a directed acyclic graph (DAG) and conditional probability tables (CPT) which define the probability of a node given all potential combinations of its parent nodes (Yang and Frangopol, 2018). Each node holds a finite number of states which cannot occur simultaneously and arcs which are used to connect multiple nodes indicate direct probabilistic relationships.

BNs, also known as belief networks, are based on the application of the Bayes theorem to calculate conditional probabilities. The network is normally built from existing data or expert opinion on the variables of consequence and the dependencies between them (Kammouh *et al.*, 2020). The Bayes theorem is

based on the knowledge that observations about the end result of a system process must change when new evidence is introduced. BNs can be applied towards decision-making problems based on prior knowledge about system operation (Adedipe *et al.*, 2020). A simple BN structure is shown in Figure 5.2.

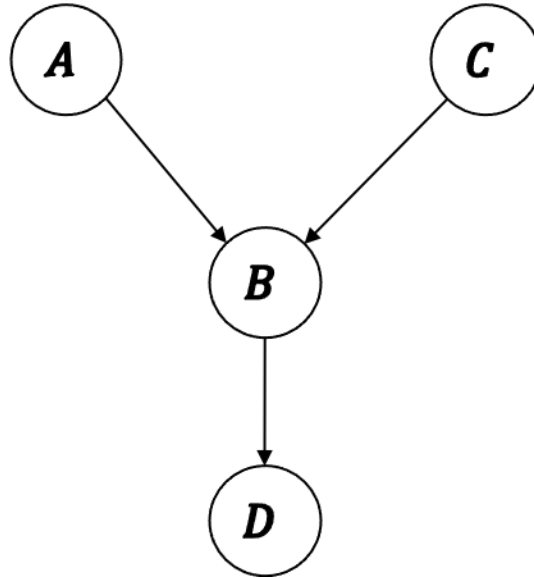


Figure 5.2 Simple representation of BN

In Bayes theorem, posterior probability of an event can be expressed in terms of its prior probability, likelihood function and normalisation constant. This can be expressed mathematically as:

$$P(A|B) = \frac{P(B|A) \times P(A)}{P(B)} \quad (5-1)$$

where $P(A|B)$ is the posterior probability and constitutes the belief of A occurring given the observation of evidence B , $P(B|A)$ signifies the likelihood of B being observed given that the event A holds true, $P(B)$ represents the probability of the evidence occurring and $P(A)$ is the prior probability.

Dynamic Bayesian networks (DBN) are an extension of BNs which provide an explicit time dimension. The DBN approach allows a system operation to be modelled as dynamic, expanding the power of analyses by including common causes and multi-state variables (Ashrafi and Zadeh, 2017). A DBN is a transition model based on random probability distribution splintered over a set of random

variables, over which a collection of conditional probability assumptions is defined. The feature of time-invariance also ensures that the variable dependency model remains unchanged at any time. The term “dynamic” is adopted as an attachment to BN when multiple time slices are needed to accurately represent the evolution of the system through time (Montani *et al.*, 2008). Due to a DBN being analogous to a semi-Markovian random process with order $t - 1$, a local BN is extended to t number of time slices when $t = 2$. Such models are referred to as “two-time-slice temporal Bayesian network” or 2-TBN (Montani *et al.*, 2008). A general structure of a DBN is shown in Figure 5.3.

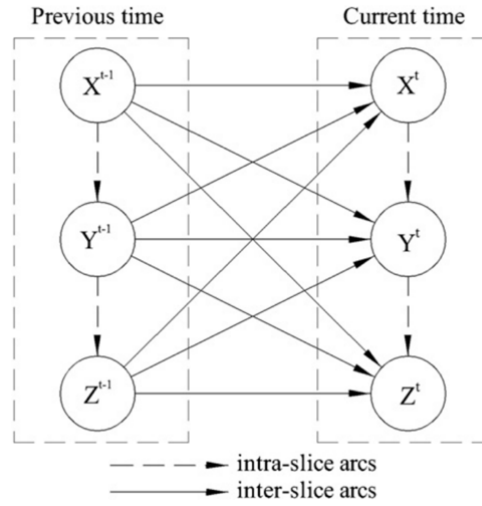


Figure 5.3 Typical structure of a DBN (Cai *et al.*, 2013)

If B_1 is a Bayes net that represents the prior probability distribution of variable states $P(Z_1)$ and $B_{\rightarrow}$ is a Two-Timeslice BN (2TBN) which represents $P(Z_t|Z_{t-1})$, a DBN can be defined as $(B_1, B_{\rightarrow})$ by means of a DAG as (Murphy, 2002):

$$P(Z_t|Z_{t-1}) = \prod_{i=1}^N P(Z_t^i | \text{Pa}(Z_t^i)) \quad (5-2)$$

where Z_t^i represents the i th node at time t , and $\text{Pa}(Z_t^i)$ are the parent nodes of (Z_t^i) within the network which can be in the same or preceding time slice. The joint distribution of a DBN can be obtained by expanding the 2TBN into T number of time slices, as follows:

$$P(Z_{1:T}) = \prod_{t=1}^T \prod_{i=1}^N P(Z_t^i | \text{Pa}(Z_t^i)) \quad (5-3)$$

In the context of wind energy, BNs have been applied towards reliability assessment, fault diagnosis and prognosis, and operation and maintenance (O&M) planning. BNs are adopted in reliability analysis of wind turbines due to the effect of better reliability on reduction of O&M costs which in turn leads to a reduction in levelised cost of electricity (LCOE) (Adedipe *et al.*, 2020). To this effect, Nielsen and Sorensen (2017) applied the DBN technique to integrate updates from WT blade inspection data in order to estimate its remaining useful life (RUL). With the emergence of condition monitoring (CM) and condition-based maintenance (CBM) in reliability engineering research and practice, the concept of BN as a tool for fault detection has warranted further exploration.

Furthermore, to avoid the computational complexities associated with calculating conditional probabilities for large networks, software packages such as Netica (Norsys Software Corporation, 2019), WinBUGS (Griffin and Steel, 2007), Hugin (Nielsen and Sørensen, 2010) and MSBN (Kadie *et al.*, 2001) have been developed to create and manipulate BNs and their different variations. For this study, the Netica software application has been used.

5.4 DBN Model Development

In this section, a DBN model is developed for reliability as well as fault diagnosis of the OWT gearbox taking into account the degradation of its subassemblies over time. The DBN model has been divided into three layers: the fault layer, the subassembly layer and the system layer. The model is broken down to the fault layer in order to highlight the progression from a fault to the failure of the gearbox system. The system layer consists of the gearbox which has been divided based on modular composition into five assets in the subassembly layer which are critical to the reliable operation of the gearbox. These subassemblies include the gears, bearings, lubrication system, housing and shaft. The subassembly layer is further broken down to the fault layer which shows the different avenues through which each subassembly can fail. The nodes in the fault layer are referred to as

the root nodes as they have no parents. The manifestation of one of the failure modes triggers the failure of its associated subassembly which in turn leads to the failure of the gearbox system.

The system was modelled to go through four stages of degradation which were represented as four time slices and were denoted by $T = 0, T = 1, T = 2$ and $T = 3$. The progression of the root nodes in the DBN model between degradation states follows Weibull distribution as it can be used to represent system deterioration (Dinwoodie *et al.*, 2012; Douard *et al.*, 2012; Le and Andrews, 2016b). The degradation factor of each failure mode in the DBN is determined from the reliability function of the analogous 2-parameter Weibull distribution. This is given below as Nielsen (2011):

$$f(t|\gamma, \beta) = \gamma/\beta t^{(\gamma-1)} \exp\left\{-\left(\frac{t}{\beta}\right)^\gamma\right\}, \text{ for } \gamma > 0, \text{ and } \beta > 0, \quad (5-4)$$

where γ represents the shape parameter and β represents the scale parameter. The failure rates which were used as the basis for gearbox Weibull distributions (life data) were obtained from Smolders *et al.* (2010) and Bhardwaj *et al.* (2019). For ease of computation, it was assumed that the degradation parameters for each time slice are identical.

Table 5.2 Life data for gearbox subassemblies

Failure modes	Subsystem	T=1 (hours)	T=2 (hours)	T=3 (hours)	Subsystem repair time (hours)
Gear teeth fail	Gear	$\beta=0.96$ $\gamma=1057.79$	$\beta=0.96$ $\gamma=1057.79$	$\beta=0.96$ $\gamma=1057.79$	12
Gear teeth slip		$\beta=1.07$ $\gamma=1921.36$	$\beta=1.07$ $\gamma=1921.36$	$\beta=1.07$ $\gamma=1921.36$	
Abnormal noise		$\beta=1.46$ $\gamma=347.55$	$\beta=1.46$ $\gamma=347.55$	$\beta=1.46$ $\gamma=347.55$	
Loss of function	Bearings	$\beta=1.00$ $\gamma=15.86$	$\beta=1.00$ $\gamma=15.86$	$\beta=1.00$ $\gamma=15.86$	12
Bearings ring creep		$\beta=0.98$ $\gamma=100.01$	$\beta=0.98$ $\gamma=100.01$	$\beta=0.98$ $\gamma=100.01$	
Abnormal noise		$\beta=0.99$ $\gamma=98.35$	$\beta=0.99$ $\gamma=98.35$	$\beta=0.99$ $\gamma=98.35$	

Misalignment		$\beta=0.99$ $\gamma=98.35$	$\beta=0.99$ $\gamma=98.35$	$\beta=0.99$ $\gamma=98.35$	
Overheating		$\beta=0.99$ $\gamma=97.55$	$\beta=0.99$ $\gamma=97.55$	$\beta=0.99$ $\gamma=97.55$	
Loss of function	Lubrication System	$\beta=1.01$ $\gamma=51.16$	$\beta=1.01$ $\gamma=51.16$	$\beta=1.01$ $\gamma=51.16$	4
Fracture in housing	Housing	$\beta=1.03$ $\gamma=440.14$	$\beta=1.03$ $\gamma=440.14$	$\beta=1.03$ $\gamma=440.14$	12
Leakage		$\beta=0.99$ $\gamma=360.74$	$\beta=0.99$ $\gamma=360.74$	$\beta=0.99$ $\gamma=360.74$	
Fatigue and fracture	Shaft	$\beta=0.99$ $\gamma=121.54$	$\beta=0.99$ $\gamma=121.54$	$\beta=0.99$ $\gamma=121.54$	12
Bending/deflection		$\beta=0.99$ $\gamma=162.23$	$\beta=0.99$ $\gamma=162.23$	$\beta=0.99$ $\gamma=162.23$	
Surface finish degradation		$\beta=0.99$ $\gamma=237.51$	$\beta=0.99$ $\gamma=237.51$	$\beta=0.99$ $\gamma=237.51$	
Misalignment		$\beta=1.01$ $\gamma=439.15$	$\beta=1.01$ $\gamma=439.15$	$\beta=1.01$ $\gamma=439.15$	

To incorporate CBM, a repair action was introduced at the first stage of degradation and a failure occurs, i.e., at time slice $T = 1$. This was done through addition of decision and utility nodes to the DBN model to form an influence diagram (ID). A decision node is a type of node which presents different options of decisions which can be taken. This node can have a direct impact on chance nodes and can also have certain associated costs which are represented by utility nodes (Yang & Frangopol, 2018). The effects of CBM on reliability of the gearbox system are described further in section 5.4.4.

The local BN models which represent the gearbox assembly are based on the causal relationship between the performance of the subassemblies and that of the gearbox. These BN models are then connected by time-based arcs to incorporate time dependence. Each subsystem is represented by a nature node with two states:

- “Yes”, which signifies the reliability of the subassembly/assembly, and
- “No”, which signifies the probability of failure.

The representation of the unexpanded Netica model can be seen in Figure 5.4.

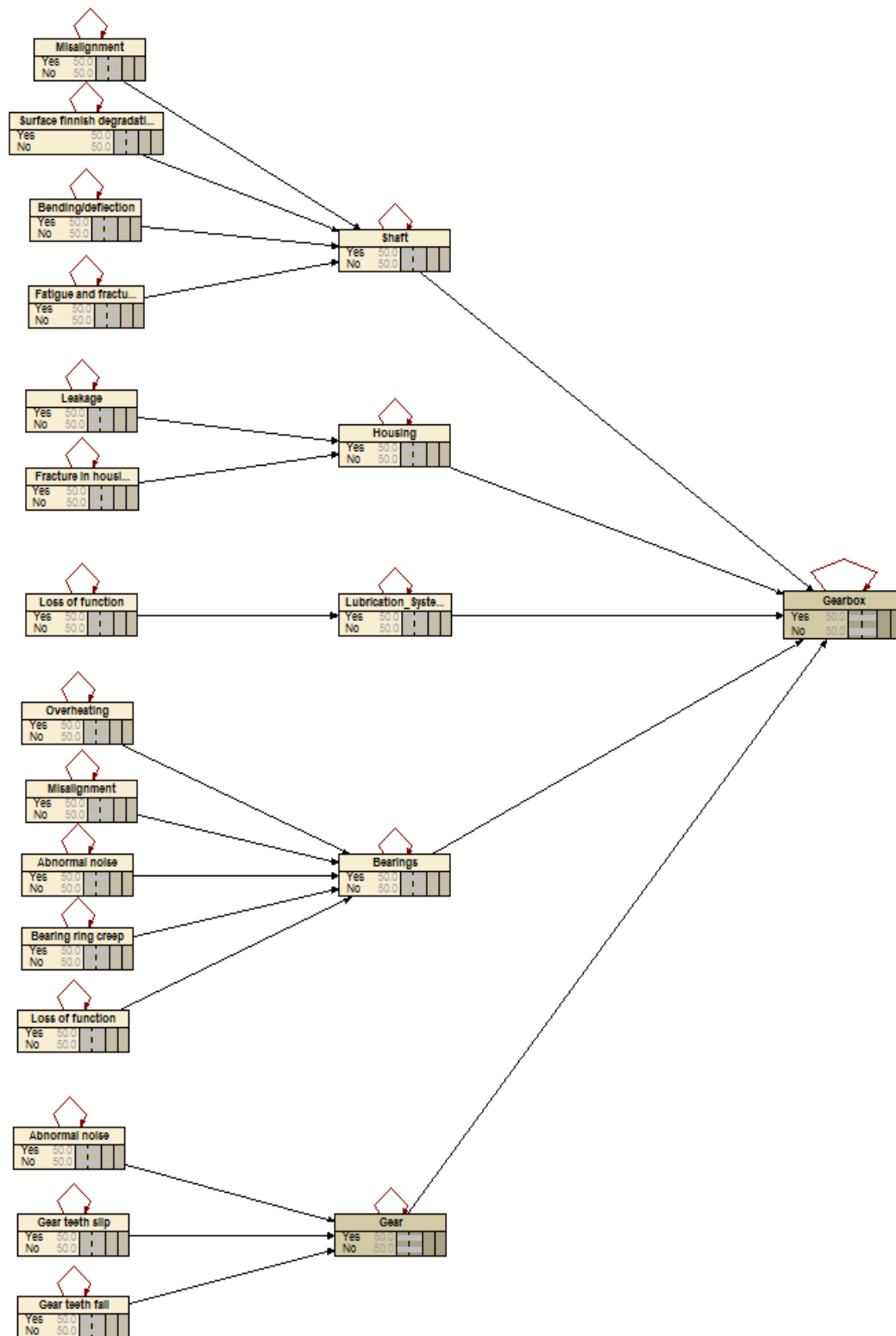


Figure 5.4 Unexpanded DBN Model

The conditional probability tables (CPTs) for gearbox system performance have been generated for the subassembly and system layers to complete the BN model. They represent the relationship between the failure modes and each subassembly and the relationship between the subassemblies and the gearbox system respectively.

Table 5.3 - Table 5.7 present the conditional probability tables for each of the subassemblies and the system.

Table 5.3 CPT of gearbox subassembly performance

Gear teeth fail	Gear teeth slip	Abnormal noise	P (Gear = 1)
1	1	1	1
1	1	0	0
1	0	1	0
1	0	0	0
0	1	1	0
0	1	0	0
0	0	1	0
0	0	0	0

Table 5.4 CPT of Bearings Subassembly Performance

Loss of function	Bearing ring slip	Abnormal noise	Misalignment	Overheating	P (Bearings = 1)
1	1	1	1	1	1
1	1	1	1	0	0
1	1	1	0	1	0
1	1	1	0	0	0
1	1	0	1	1	0
1	1	0	1	0	0
1	1	0	0	1	0
1	1	0	0	0	0
1	0	1	1	1	0
1	0	1	1	0	0
1	0	1	0	1	0
1	0	1	0	0	0
1	0	0	1	1	0

1	0	0	1	0	0
1	0	0	0	1	0
1	0	0	0	0	0
0	1	1	1	1	0
0	1	1	1	0	0
0	1	1	0	1	0
0	1	1	0	0	0
0	1	0	1	1	0
0	1	0	1	0	0
0	1	0	0	1	0
0	1	0	0	0	0
0	0	1	1	1	0
0	0	1	1	0	0
0	0	1	0	1	0
0	0	1	0	0	0
0	0	0	1	1	0
0	0	0	1	0	0
0	0	0	0	1	0
0	0	0	0	0	0

Table 5.5 CPT of Lubrication System Performance

Loss of function	P (Lubrication system = 1)
1	1
0	0

Table 5.6 CPT of Housing Subassembly Performance

Fracture in housing	Leakage	P (Housing = 1)
1	1	1
1	0	0
0	1	0
0	0	0

Table 5.7 CPT of Shaft Subassembly Performance

Fatigue and fracture	Bending/deflection	Surface finish degradation	Misalignment	P (Shaft = 1)
1	1	1	1	1
1	1	1	0	0
1	1	0	1	0
1	1	0	0	0
1	0	1	1	0
1	0	1	0	0
1	0	0	1	0
1	0	0	0	0
0	1	1	1	0
0	1	1	0	0
0	1	0	1	0
0	1	0	0	0
0	0	1	1	0
0	0	1	0	0
0	0	0	1	0
0	0	0	0	0

The data obtained from the DBN analysis of the gearbox system is then used as input for further analysis using the BlockSim® software tool.

5.5 Results and analysis

5.5.1 Reliability analysis

The reliability of a system is described as the ability of that system to perform its desired functions, for a specific time and under specific conditions (BSI, 2016). The reliability of the OWT gearbox, given that it is a series system, can be calculated as:

$$R(t) = \prod_{i=1}^n R_i(t) \quad (5-5)$$

where n is the number of components and $R_i(t)$ indicates the reliability of the component i within the system. The transient reliability function plot for the entire gearbox system is shown in Figure 5.5.

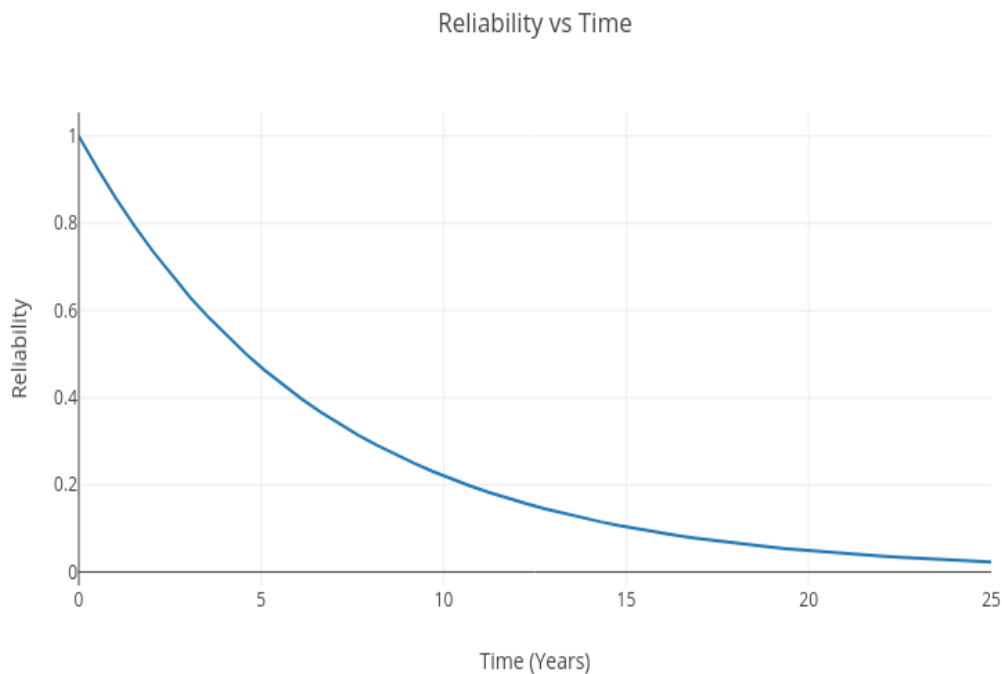


Figure 5.5 Reliability plot for gearbox over its lifetime

As can be seen, the reliability of the system gradually decreases until it reaches a value of 0.0228 at 25 years. This result signifies that, as expected, the system will successfully perform its desired function until the probability that it does so eventually drops to zero. The reliability of each subassembly over the gearbox lifespan was also determined and is shown in Figure 5.6.

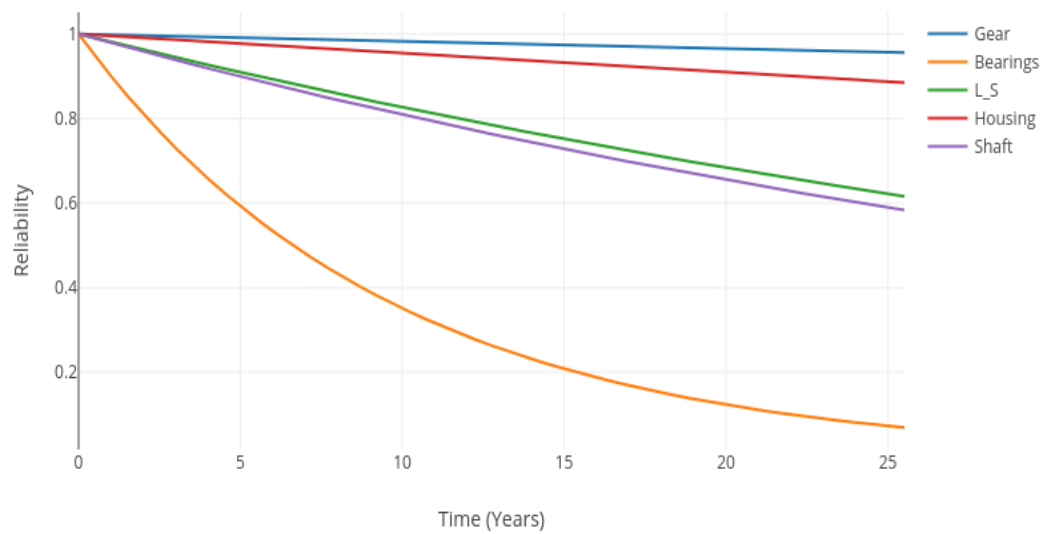


Figure 5.6 Reliability plot for gearbox subassemblies over its lifetime

The mean availability of the gearbox over its lifetime was obtained and can be seen in Figure 5.7. The mean availability is defined as the proportion of time in which the system is able to operate during a given time period. As can be seen, the availability drops in the first seven years of operation before stabilising at a value 0.99981 over the rest of the gearbox's operating lifetime.

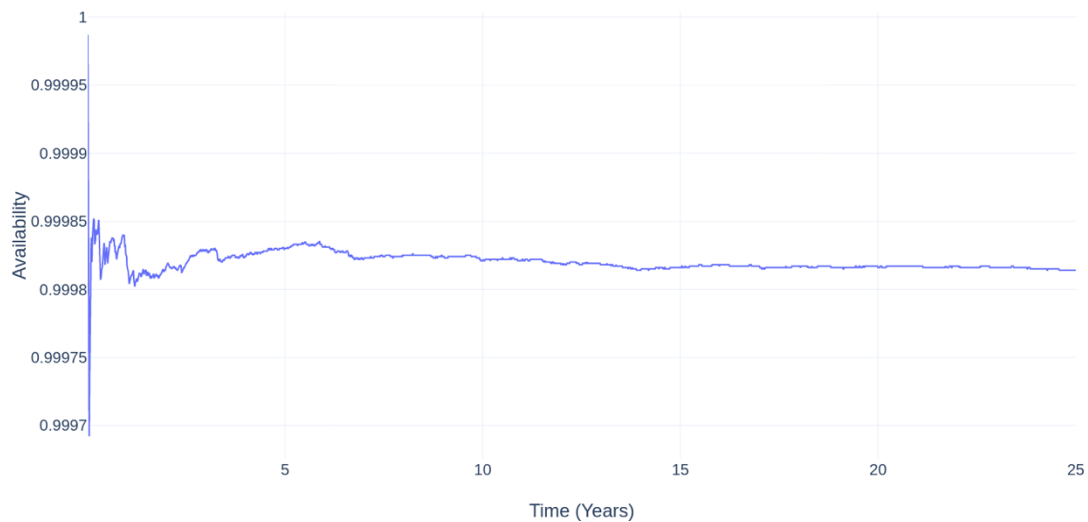


Figure 5.7 Availability of the gearbox system over its lifetime

The mean time between failure (MTBF), which is calculated as the total time the system should be in operation divided by the number of times maintenance

interventions have been performed on the system, is obtained for the entire gearbox system. Mathematically, this can be represented as:

$$MTBF = \frac{T}{M} \quad (5-6)$$

where T represents the total time that the gearbox should be in operation and M represents the number of maintenance interventions performed on the system during its 25-year lifespan. M is calculated mathematically using the equation:

$$M = \int_0^T \lambda(t) \quad (5-7)$$

where $\lambda(t)$ is the rate of occurrence of failure at time t . Over its 25-year lifetime, the gearbox is expected to experience functional failure for approximately 3.8 times, meaning that maintenance/repair action will occur approximately 3.8 times. The MTBF is therefore calculated as 6.5 years.

5.5.2 Fault diagnosis

As stated previously, the BN technique has the ability to perform both forward and backward analyses, otherwise known as predictive and diagnostic analysis respectively. Fault diagnosis is performed on the gearbox system through backward analysis of the DBN model. As faults are known to contribute to the deterioration in performance of complex mechanical systems, fault diagnosis plays an important part in identifying and isolating faults (Ren *et al.*, 2015).

Fault diagnosis through BN backward analysis is performed by following the direction of arcs from child nodes back to their parent nodes, i.e., moving from effect to cause (Kabir and Papadopoulos, 2019). This analysis involves obtaining new beliefs (posterior probabilities) about any node given the introduction of new evidence. It is important to note that this method of fault diagnosis can only present the probability of a fault occurring. The higher the posterior probability of the fault node, the more likely it is that the corresponding fault has occurred (Liu *et al.*, 2020).

In this model, if evidence of system failure is presented at time slice $T=1$ (i.e., the “No” state at the gearbox node = 100% or 1), the posterior probabilities at the fault and subassembly layer are updated. As can be seen in Figure 5.8, the node with the highest probability of failure is the loss of function for the bearings subassembly, identifying this as the most probable cause of system breakdown/failure across all time slices.

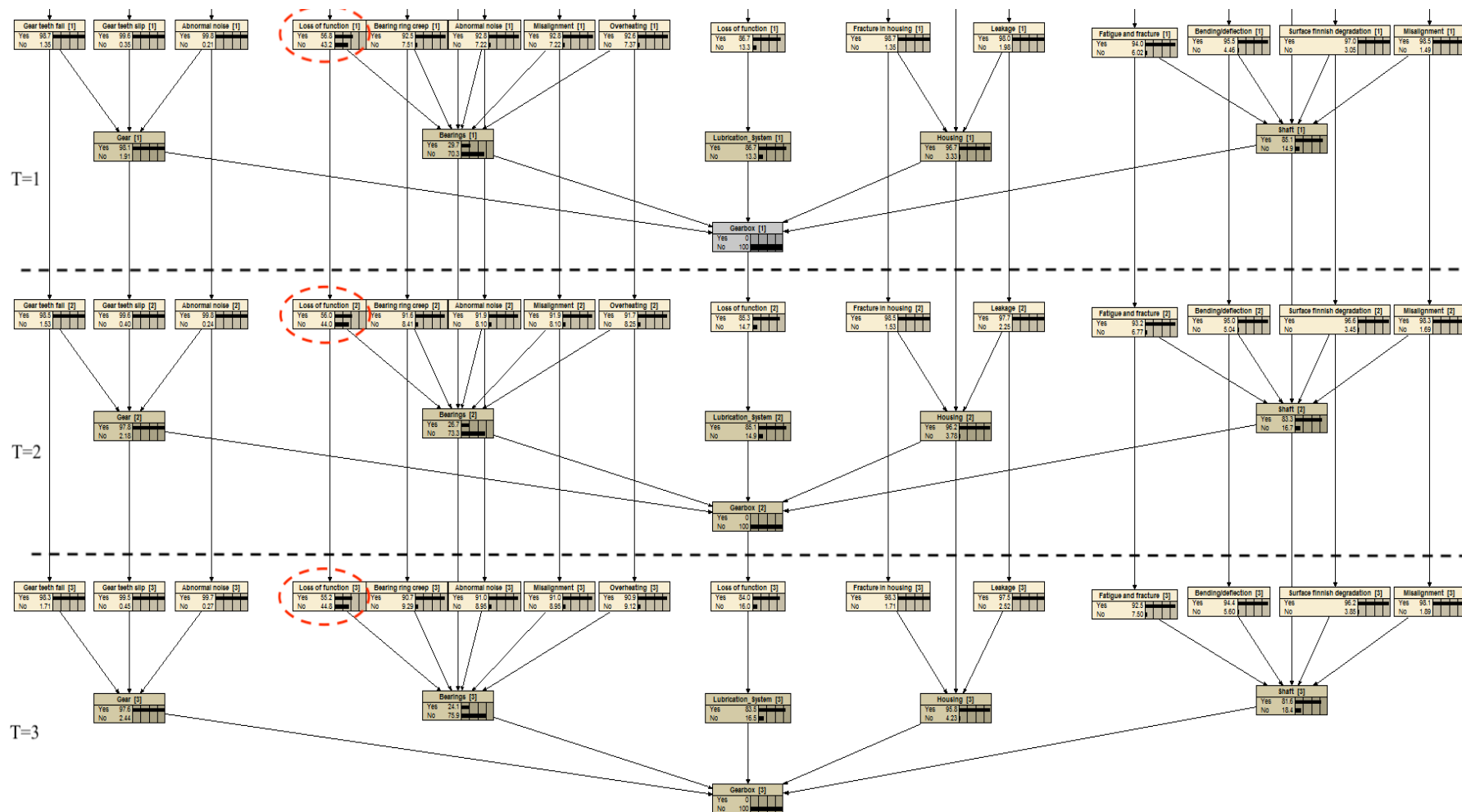


Figure 5.8 Backward analysis (diagnosis) of gearbox system

5.5.3 Reliability importance

The reliability importance of each gearbox subassembly is also obtained in order to determine the effect of the reliability of each subsystem on the entire gearbox system. Analysing the importance of individual subassemblies to system reliability is imperative for a variety of reasons such as scheduling of maintenance activities, determining the cause of system breakdowns, and expansion planning (Daemi *et al.*, 2012).

The importance of each subassembly in this DBN model is performed by obtaining the difference between the prior and posterior probabilities for each subassembly when evidence of system failure at the final time slice (i.e., the “No” state at the gearbox node = 100% or 1 at T=3) is introduced. The higher the difference, the higher the importance. The prior and posterior probabilities for each subsystem at each time slice can be seen in Table 5.8 and presented in Figure 5.9.

Table 5.8 Prior and posterior probabilities of all gearbox subsystems in each time slice

Subassembly		T = 1		T = 2		T = 3	
		Prior	Posterior	Prior	Posterior	Prior	Posterior
Gear	Yes	0.9973	0.9926	0.9946	0.9853	0.9919	0.9780
	No	0.0027	0.0074	0.0054	0.0047	0.0081	0.0220
Bearings	Yes	0.9017	0.7290	0.8110	0.4850	0.7310	0.2660
	No	0.0993	0.2710	0.1890	0.5150	0.2690	0.7340
Lubrication System	Yes	0.9812	0.9487	0.9628	0.8980	0.9447	0.8490
	No	0.0188	0.0513	0.0372	0.1020	0.0553	0.1510
Housing	Yes	0.9953	0.9872	0.9906	0.9744	0.9860	0.9618
	No	0.0047	0.0128	0.0094	0.0256	0.0140	0.0382

Shaft	Yes	0.979 0	0.9426	0.9584	0.8860	0.8860	0.8310
	No	0.021 0	0.0574	0.0416	0.1140	0.1140	0.1690

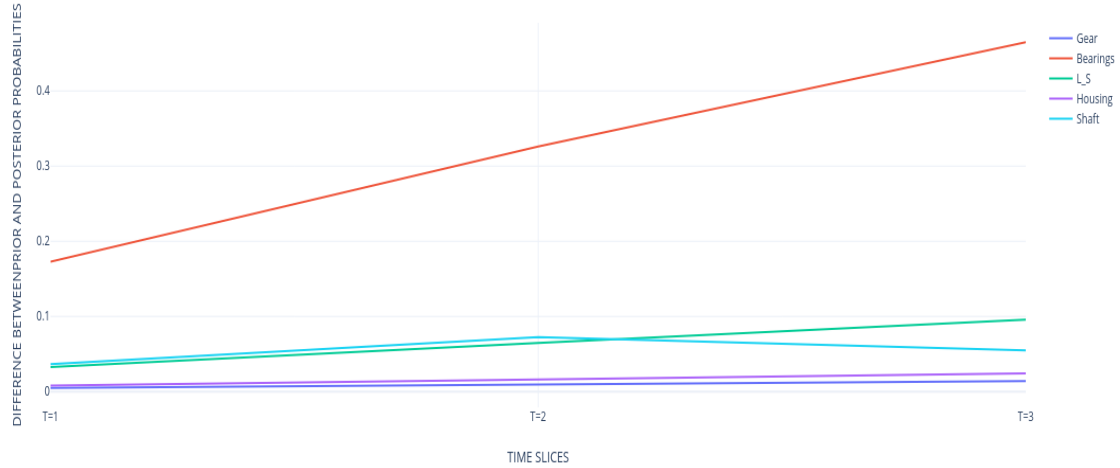


Figure 5.9 Difference between prior and posterior probabilities

As can be seen, the bearings subassembly has the highest probability difference value, followed by the shaft, lubrication system, housing and eventually the gear subassemblies. This order is confirmed by the failure criticality index, which identifies and ranks the impact that each subsystem has on the overall gearbox failure. This can be expressed mathematically as:

$$FCI_i = \frac{\text{Number of failures caused by subsystem } i \text{ in } (0, t)}{\text{Number of BOP system failures in } (0, t)} \quad (5-8)$$

Figure 5.10 depicts the FCI for the gearbox system which confirms that the bearings subsystem has the highest index, followed by the shaft, lubrication system, housing and gear. This is consistent with the outcome of the study on wind turbine gearbox failures performed by Sheng (2014) and the study on the reliability of floating offshore wind turbines conducted by Li *et al.*, (2020) which showed that 70% of gearbox failures are attributable to bearings.

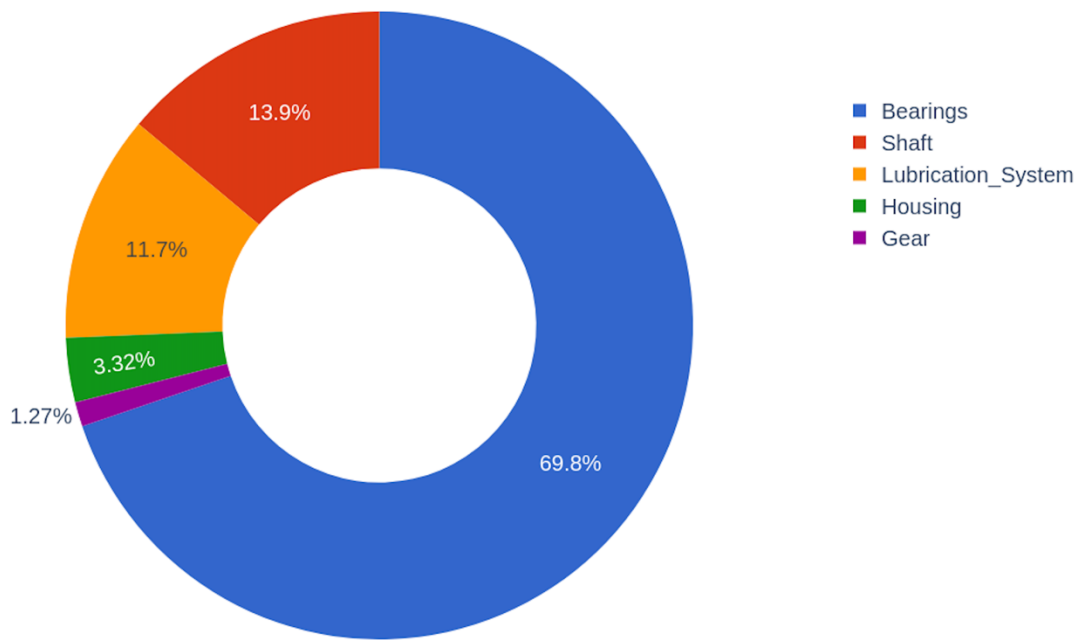
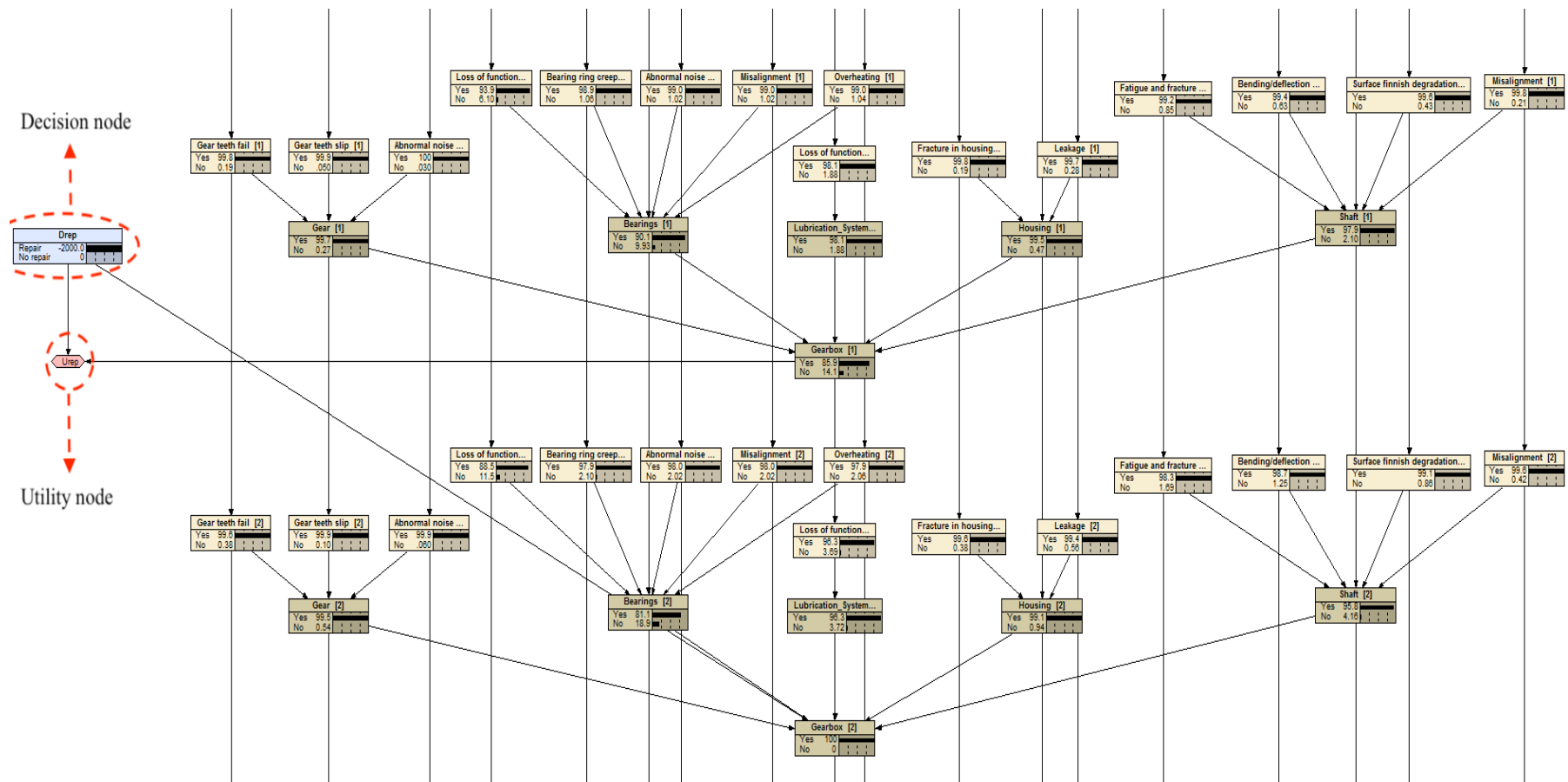


Figure 5.10 Failure criticality index for gearbox system

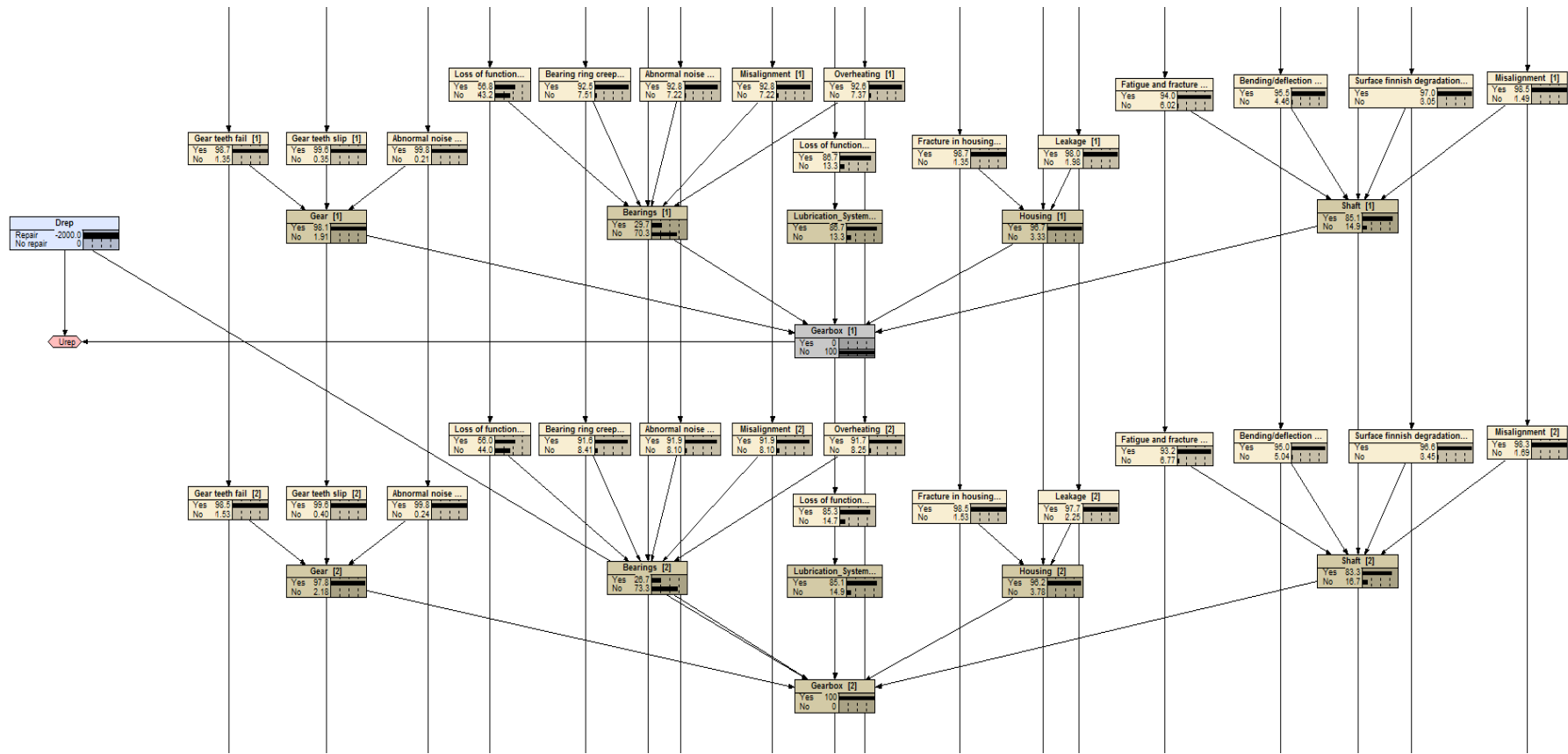
5.5.4 Incorporation of Condition-based maintenance

CBM is introduced through the addition of decision and utility nodes to the DBN model to form an influence diagram (ID). A decision node is a type of node which presents different options of decisions which can be taken. This node can have a direct impact on chance nodes and can also have certain associated costs which are represented by utility nodes (Yang and Frangopol, 2018).

As shown in Figure 5.11, if evidence of failure in the time slice $T=1$ is introduced, and the decision is made to repair (represented by the decision node D_{rep}), the reliability of the gearbox in time slice $T=2$ (the “Yes” state in Gearbox [2]) increases to 100%. This is because the assumption is made that perfect maintenance is performed to take the gearbox system back to its original state. The utility of performing repair action, which is the negative value of its relative cost, is represented by utility node U_{rep} and assumed to be $U_{rep} = -1000$ for this analysis. The value of -1000 for U_{rep} is representative and does not factor into the reliability analysis and fault diagnosis.



(a)



(b)

Figure 5.11 Gearbox system performance (a) without evidence of CBM (b) with evidence of CBM

5.5.5 Sensitivity analysis

A sensitivity analysis has been performed to determine how changes in key metrics such as coverage factor and redundancy affect the performance of the gearbox. The coverage factor, which refers to the percentage of faults that can be detected in any engineering system while it is being monitored, is an important measure in assessment of how effective condition monitoring is (Animah *et al.*, 2018).

The effects of coverage factor on reliability, availability, MTBF, and expected number of failures were determined. Figure 5.12 shows the transient reliability plots for the gearbox system at 100%, 80%, 60%, 40%, and 20% coverage factors. As can be seen, reliability of the gearbox decreases to zero faster with decreasing coverage factors.

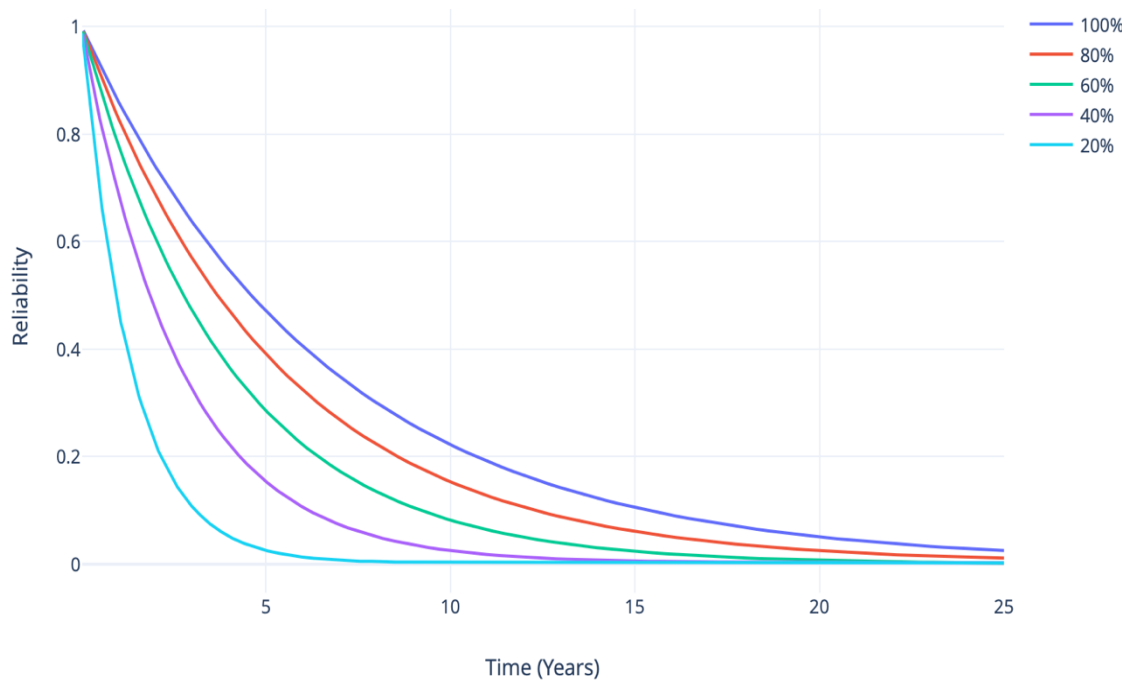


Figure 5.12 Effect of 100%, 80%, 60%, 40%, and 20% coverage factor on system reliability

The effect of coverage factor on mean availability can be seen in Table 5.9. As can be seen, mean availability reduces with decreasing coverage factor, underscoring the importance of adequate fault detection.

Table 5.9 Effect of coverage factor on availability

Coverage factor (%)	Availability
100	0.99981
80	0.99976
60	0.99968
40	0.99952
20	0.99904

The effect of the coverage factor on the MTBF was also analysed. It can be seen from Table 5.10 that the MTBF decreases with decreasing coverage factor. This signifies that the amount of time in which the system is in operation decreases as fault detection capacity declines.

Table 5.10 Effect of coverage factor on MTBF

Coverage factor (%)	MTBF (Years)
100	6.58
80	5.15
60	3.91
40	2.58
20	1.29

Table 5.11 shows the effect of coverage factor on the expected number of failures. As can be seen, with decreasing coverage factor, the expected number of failures increases with decreasing coverage factor. This shows that the lower level of fault detection leads to a higher number of system failures.

Table 5.11 Effect of coverage factor on expected number of failures

Coverage factor (%)	Expected number of failures
100	3.8
80	4.8
60	6.4
40	9.6
20	19.2

The effect of redundancy on the MTBF was also analysed by introducing a second bearing subsystem. Redundancy has a clear effect on MTBF as it is seen to increase MTBF from 6.5 years to 21.9 years, further underscoring the importance of the bearings subassembly on the gearbox performance. The introduction of redundancy also leads to a decrease of the expected number of failures in the gearbox lifetime from 3.8 times to 1.1 times.

5.6 Conclusion and further works

This paper presented a reliability and fault diagnosis model based on dynamic Bayesian network for an offshore wind turbine gearbox while incorporating degradation and condition-based maintenance. The gearbox was divided into five subassemblies connected in series with each other. The reliability, availability and mean time between failures of the gearbox system over its lifetime have been estimated. Fault diagnosis of the OWT gearbox has been performed and the reliability importance and failure criticality index were determined using dynamic Bayesian Network. The bearing subassembly was determined to be the least reliable component, confirmed by it having the highest failure criticality index as well as the highest difference between prior and posterior probabilities over time. This was then followed by the shaft, lubrication system, housing and gears. The fault diagnosis showed that loss of function in the bearing subassembly is the most likely root cause for the gearbox failure. A sensitivity analysis was also performed to determine the effect of fault coverage factor on reliability, availability and mean time between failures and the effect of redundancy on mean time between failures. Results showed that coverage factor, which represents the quality of condition monitoring, and redundancy in the form of an extra bearings

subassembly, have a considerable effect on system performance. A decrease in coverage factor directly correlated with decreases in reliability, availability and mean time between failures. With the introduction of redundancy also comes an increase in mean time between failures.

For future research, a number of opportunities are available. Lessons learned from the present reliability analysis and fault diagnosis of the offshore wind turbine gearbox can be applied to other multi-component systems within and without the drivetrain in order to more robustly analyse their performance. Another opportunity for further work can be to apply the Bayesian network-based approach to reliability analysis while taking into account imperfect repair and common-cause failures.

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6 OPERATION AND MAINTENANCE PLANNING OF FLOATING OFFSHORE WIND TURBINES USING STOCHASTIC PETRI NETS

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Statement of contribution:

Tobiloba Elusakin was responsible for study conceptualisation, methodology, software, validation, formal analysis, investigation, data curation, writing - original draft, review and editing, visualisation and project administration. Dr Mahmoud Shafiee was responsible for study conceptualisation, methodology, software, validation, formal analysis, investigation, review and editing, visualisation and supervision. Tosin Adedipe was responsible for writing - review and editing.

Abstract

With increasing deployment of offshore wind farms further from shore and in deeper waters, the efficient and effective planning of operation and maintenance (O&M) activities has received considerable attention from wind energy developers and operators in recent years. The O&M planning of offshore wind farms is a complicated task, as it depends on many factors such as asset degradation rates, availability of resources required to perform maintenance tasks (e.g., transport vessels, service crew, spare parts, and special tools) and the uncertainties associated with weather and climate variability. A brief review of the literature shows that a lot of research has been conducted on optimising the O&M schedules for fixed-bottom offshore wind turbines, whereas the literature for O&M planning of floating wind farms is too limited. This paper presents a stochastic Petri network (SPN) model for O&M planning of floating offshore wind turbines (FOWTs) and their support structure components, including floating platform and mooring and anchoring systems. The proposed model incorporates all interrelationships between different factors influencing O&M planning of FOWTs, including deterioration and renewal process of components within the system. Relevant data such as failure rate, mean-time-to-failure (MTTF), degradation rate, etc. are collected from the literature as well as

wind energy industry databases, and then the model is tested on an NREL 5-MW reference wind turbine system mounted on an OC3-Hywind spar buoy floating platform. The results indicate that our proposed model can significantly contribute to the reduction of O&M costs in the floating offshore wind sector.

6.1 Introduction

The wind energy industry is expanding its frontiers throughout the world, with wind power gradually increasing its share in the global energy mix. According to statistics from WindEurope, the total installed capacity of wind power in the European Union (EU) had reached 205 gigawatts (GW) by the end of year 2019. This capacity generated 417 terawatt hours (TWh) of electricity, covering around 15% of the EU's electricity consumption in 2019 (Wind Europe, 2020). The European Commission (EC) recognised wind energy development, with a focus on offshore wind energy resources, as one of the strategic priorities for a low-carbon future (European Commission, 2016; Hernandez *et al.*, 2017).

Offshore wind is considered the future of wind energy in the UK, and the government has recently set out commitments to ensure that offshore wind will have the capacity to power every home in the country by 2030. This boosts the government's previous offshore wind capacity target from 30GW to 40GW (GOV.UK, 2020). According to the Crown Estate (2019), the UK currently has the largest operational capacity of offshore wind in Europe, representing 45% of all installations. This was achieved by installing more than 1,764 MW offshore wind power by the UK (out of a total 3,627 MW in Europe) in 2019 (Wind Europe, 2020). Although the growth in capacity has naturally led to a reduction in the levelized cost of electricity (LCOE) from offshore wind, it has drastically increased the operating expenditure (OPEX) for the wind farms (Shafiee *et al.*, 2016).

With the increasing number of offshore wind installations and due to limited space available near the coast in shallow waters, there is now a crucial need to move to deeper waters where wind speeds tend to be higher and more consistent (Shafiee, 2015). Despite these benefits, the deepwater wind farms have to deal with a greater scale of challenges than shallow-water wind farms, such as the design constraints of fixed-bottom structures, a wide variation of weather

conditions, and the need to hire expensive machinery or access equipment for the maintenance (Shafiee *et al.*, 2020). To overcome some of these challenges, floating offshore wind turbines (FOWTs) are being developed and promoted as an economically attractive option for wind energy projects in water depths greater than 60 meters. As FOWTs are not rigidly fixed to the seabed and have been designed to cope with severe wave conditions, they are not limited in their location to just shallow waters (Guo *et al.*, 2015).

On a global scale, Europe has been at the fore front of floating wind energy developments (Carbon Trust, 2015). The wind energy industry's research and development programs have mainly focused on improving wind farms' layouts, as well as designing floating foundations to optimise the deepwater wind energy production. The floating offshore wind concepts of Hywind, WindFloat and SWAY, which are shown in Figure 6.1, are among the most common technologies being tested and deployed in real-world settings (Roddier *et al.*, 2009). Some other examples of floating wind concepts include: Blue H, WindSea, Nova, Vertax and Vertiwind (Jonkman and Matha, 2011). There have been some research studies and pilot programs to test these concepts in controlled offshore environments. These research studies have been aimed at improving the materials properties of wind turbines and optimising the maintenance processes required for an improved floating offshore wind farm energy generation.



(a)

(b)

(c)

Figure 6.1 Floating offshore wind concepts: (a) Hywind (Equinor, 2018) (b) WindFloat (Principle Power, 2015) and (c) SWAY (Sway Concept, 2012).

Floating wind energy will be necessary for the UK to meet net-zero emissions by 2050. In addition, it can create 17,000 jobs and generate £33.6 billion for the UK economy (Scottish Renewables, 2019). Recently, the UK government has set a target of 1 GW floating wind energy capacity by 2030, which is nearly 15 times the current operational capacity worldwide. There are several opportunities to deploy floating wind technologies off the coast of Scotland and Wales. Hywind Scotland is the world's first commercial floating offshore wind farm located 25km off the coast of Peterhead in Aberdeenshire. The wind farm comprises six 5MW floating wind turbines which will produce enough electricity to power 20,000 homes (Equinor, 2018). The Kincardine project is the largest floating offshore wind farm in the world by proposed capacity which is under construction about 15km off the coast of Aberdeen at water depths ranging from 60 to 80 metres. The wind farm comprises one 2 MW and five 9.525 MW Vestas wind turbines which are being installed on triangular-shaped semi-submersible foundations (Durakovic, 2020).

The high cost of O&M is a major area of concern to wind energy developers and operators. Depending on the wind farm characteristics, such as the number and power rating of wind turbines, distance to shore, weather and sea state, etc. there

will be different cost implications (Shafiee *et al.*, 2016). Improvements in the O&M planning of offshore wind farms could lead to considerable reduction in costs. According to Carbon Trust (2015), the O&M planning is known as one of the technical barriers for floating offshore wind farms in deep waters and harsh weather conditions. Therefore, there is a need for innovations in methods and practice that improve O&M planning of floating offshore wind farms to increase availability and safety and lower O&M expenditure. An example of innovation campaigns in the wind energy sector is the UK's Offshore Wind Innovation Hub, which was set up to coordinate UK innovation and technology development in wind energy businesses, with a focus on offshore wind energy cost reduction.

The O&M planning of floating offshore wind farms is a complicated task due to the diversity of components such as wind turbine parts, foundation platform, mooring cables, anchors, etc., existence of different degradation processes with currently unknown rates, sparsity of failure data, uncertainty of weather variability, and unpredictability of demand for spare parts and maintenance vessels. A brief review of the literature in the next section shows that very few research studies have been conducted on optimising the O&M procedures for floating offshore wind farms. To overcome this research gap, this paper proposes a stochastic Petri net (SPN) model for O&M planning of FOWT systems and their associated support structure components, including floating platforms, catenary mooring lines and anchoring systems. The proposed model incorporates all interrelationships between different factors influencing O&M planning of FOWTs, including deterioration and renewal process of components within the system. Relevant data such as failure rate, mean-time-to-failure (MTTF), degradation rate, etc. have been collected from the literature as well as wind energy industry databases, and then the model tested against a NREL 5-MW reference wind turbine system with a spar-type substructure and catenary mooring lines.

The organisation of the rest of this paper is as follows. Section 6.2 reviews the O&M planning techniques and tools adopted in the offshore wind industry, in particular for FOWTs. Section 6.3 presents the SPN model for O&M planning of floating offshore wind farms. Section 6.4 presents the case study results and

discusses the findings. Finally, the paper is concluded and some ideas for future research are proposed in Section 6.5.

6.2 O&M planning for floating offshore wind farms

The O&M planning of floating offshore wind farms is significantly different than that of onshore wind farms or even bottom-fixed wind turbines in shallow water. This difference in O&M planning is mainly related to differences in the type of support structures (monopiles, gravity-based structures, tripods and jackets are types of foundation for bottom-fixed wind turbines, whereas the common concepts for floating foundations are spar-buoy, semi-submersible and tension-leg platform); presence of additional components (such as mooring lines and anchors); uncertainties associated with the components lifetime due to variations in loading and environmental conditions, etc. Figure 6.2 shows a spar-type floating wind turbine consisting of a spar buoy platform, three catenary mooring lines, tower, nacelle, and three blades.

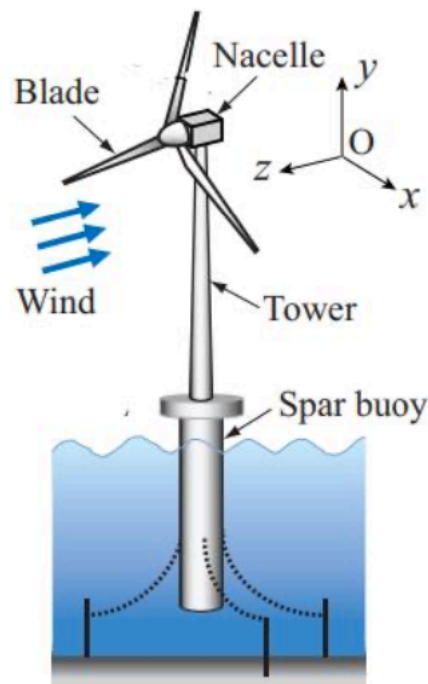


Figure 6.2 Spar-type floating offshore wind turbine

There are a number of factors that may influence the O&M schedules of floating offshore wind farms to some extent. These factors are summarised below:

- Poor accessibility due to dependence on weather conditions: access to floating offshore wind farms to carry out planned and/or unplanned maintenance tasks may be restricted due to poor weather conditions and high waves. Thus, a fixed maintenance schedule cannot provide an efficient solution for wind farm managers. The O&M planning of floating offshore wind farms requires iterative methods through which the maintenance schedules can be updated when the latest weather forecasts become available. There have been few attempts at determining maintenance strategies for offshore wind farms based on accessibility evaluation and weather conditions (e.g., Leigh and Dunnett, 2016).
- Higher failure rates of components due to harsher environment conditions: the floating wind turbines are exposed to higher cyclic loads from wind and waves, causing more mechanical stresses on the foundation platforms and mooring systems, as well as the wind turbines themselves. The complex nature of the loads on FOWTs hinders their modelling and a thorough understanding of the appropriate degradation processes is needed for an effective planning of O&M activities.
- Resource constraints to execute activities: the resources required to carry out maintenance tasks in floating offshore wind farms (e.g., crew transfer vessels) may be hired by various businesses from the onshore wind or offshore oil and gas sectors. Therefore, the resources may be limited, which will restrict the time windows of the maintenance and repair activities in floating offshore wind farms.
- Spare parts availability: spare parts should be ordered from central depots, which may be many miles away from the floating offshore wind farm. On the other hand, component redundancy is not economically feasible for FOWTs. Therefore, spare parts availability and supply is critical to reduce any possible downtime and increase power production.

- More complex and time-consuming maintenance/repair tasks: the floating wind turbines are not fixed to the seabed and are free to move under the influence of wind or tide. Performing maintenance on FOWTs is more difficult, time-consuming, and risky for the personnel involved.
- Higher O&M costs: due to higher failure rates of FOWT components (as a result of harsher environmental conditions) and the longer distances that support vessels must travel, the cost of O&M will be much higher in floating offshore wind farms.

In order to incorporate the above-mentioned factors, a number of models have been proposed in the literature (see Carroll *et al.*, (2016), Le and Andrews, (2016), Nielsen and Sørensen, 2010). These models can help predict the degradation of different components that make up wind turbines in a wind farm and estimate the times to failure of the system and then schedule maintenance activities ahead of time before failure occurs. In a recent systematic review of 246 studies, Shafiee and Sørensen (2019) presented a broad classification of techniques and tools that are applied to O&M planning of wind energy farms. The techniques used for O&M planning of floating offshore wind farms should have the capability to identify the degradation extent at which a maintenance task is to be performed. These techniques, in general, are classified into two groups of 'qualitative' and 'quantitative'. The quantitative techniques include any analysis or modelling tools that make use of mathematical or statistical models, whereas the qualitative tools are based on experiential knowledge or subjective judgment. In what follows, some of the common O&M planning tools are presented and explained.

Bayesian network (BN) models have been used in several studies for reliability analysis as well as fault diagnosis of complex engineering systems. They have been applied to offshore wind turbines as well, but the model is yet to be adapted for O&M optimisation of floating offshore wind farms (Adedipe *et al.*, 2020). BNs are useful for the dynamic risk analysis and reliability assessment of offshore wind farms, allowing for updating the O&M schedules when additional data becomes available. A Bayesian updating technique has also been proposed in

Gerbatov and Soares, (2002), to model the reliability of floating structures, however, it was not applied to floating offshore wind structures to study its applicability.

Fuzzy models are another set of models which are probabilistic in nature and are therefore applicable to a variety of real-life problems. They have been used for risk and failure mode analysis, condition monitoring and fault diagnosis of wind turbine systems. Cross and Ma (2015) used a fuzzy logic model to provide signals with ambiguous data for fault diagnosis of a wind turbine system. A downside of the model is that the output requires “defuzzification” to generate a single value from the analysis. This model is yet to be applied to O&M planning and analysis of floating offshore wind farms (Koh and Ng, 2016).

Markov models offer a high level of flexibility, for which they can be used to model the degradation processes of different wind turbine subassemblies. The complexity of a Markov model depends highly on the number of states used to represent the degradation process of each component. It has been reported that Markov models are more appropriate for modelling the fatigue damage in offshore wind turbines due to wave loading (Choy *et al.*, 2018). Li *et al.* (2019) proposed a degradation-Hidden-Markov model to assess the reliability of a wind turbine when there is limited data about the system. A drawback of Markov models is that they cannot truly represent the long-term performance of wind turbine systems, as they are built using periodic inspection data and sometimes include simplistic assumptions (Marseguerra *et al.*, 2002).

Simulation models are another category of models that have been used in past studies to evaluate and compare different O&M scenarios for wind turbines. O&M strategy options and failure rates of sub-assemblies are inputted to the model to predict the level of resources required for the execution of maintenance tasks. Some simulation tools such as Monte-Carlo simulation (MCS) can be used as a standalone tool or integrated with other tools for the analysis. As an example, Markov Chain Monte-Carlo (MCMC) model is useful in the analysis of outputs from a Markov model in order to capture the uncertainty in wind power forecasting. The Dutch Offshore Wind Energy Converter (DOWEC) project (van

Bussel and Bierboom, 2003) developed a simulator called CONTOFAX based on the MCS tool to model the O&M costs as well as availability of an offshore wind farm. The simulator reported that the largest contributor to O&M costs was the wind turbine reliability, whereas the largest contributor to availability was the weather conditions. A drawback of the simulation models is that they are heavily dependent on input data such as failure and repair data, metocean data (wind and wave data), etc. which might be unavailable for some floating offshore wind farms.

Data mining is an analysis technique which is used hand-in-hand with a condition monitoring system (CMS) for O&M planning. The CMS is reliant on the analysis of condition monitoring data and intelligent-based (IB) systems. Although data mining has been used in several studies for wind turbine fault diagnosis (e.g., Kusiak and Verma, 2012) it is yet to be applied to floating offshore wind turbines. Data mining has the potential to improve the condition monitoring and optimise the O&M planning of FOWTs.

The Petri net (PN) technique is a graphical and mathematical tool used to model the dynamic state changes in a system, such as the entire wind farm or wind turbine sub-assemblies, over time. PNs are useful for modelling the multi-state systems, where the system has a range of performance levels beyond binary states of 'working' and 'not working' (e.g., the degradation process within a system). In the past years, PNs have been applied to the wind energy industry for reliability studies. However, it also has the capability of modeling degradation processes and maintenance operations. The PN uses the Weibull distribution for time-to-failure characterization, making it useful in the case of limited/unavailable failure data (Zurawski and Zhou, 1994). Another useful characteristic of PNs is that they can be analysed using several methods like coverability trees, reachability trees, matrix equations, computer simulation analysis, state equations, etc (Murata, 1989).

PNs are flexible in the sense that depending on the output required, they may be run normally or in reverse for fault detection in subassemblies (Yang *et al.*, 2011). Another model, which is an extension of the PN model, is the stochastic activity

network (SAN). It is a stochastic model which has been used in the past to model factors contributing to the uncertainty in O&M planning, such as wind speed and wave height, and their effect on the wind turbine loading. Due to the stochastic nature of environmental changes and structural degradation, as well as the limited availability of data in the floating wind turbine sector, the PN model can be an effective tool to make estimates for the times to conduct maintenance. Previously, PNs were used only as fault diagnosis and reliability evaluation tools but they are now used to describe the structure and operation of wind turbines and also to show the relationships between the faults that may occur within the wind farm (Yang *et al.*, 2011). Because FOWTs are deployed in extreme environments, it is beneficial to have more variable states incorporated into the model, including the effects of environmental loadings on the support structures and mooring systems, and the PN model provides an avenue for this. Table 6.1 presents a summary of the comparison between the technique chosen for this study, Petri networks, and the other techniques highlighted with similar applications.

Table 6.1 Comparison of PN Technique with Other Analysis Tools

Characteristics	Other Techniques	Petri Net
Quality of output values	Fuzzy models require defuzzification to generate even a single value for analysis.	The Petri net technique does not require any extra analysis to generate outputs.
Long-term operation modelling	Markov models do not truly represent long-term WT performance as they are built using parodic inspection data and sometimes include simplistic assumption.	The Petri net technique can easily develop models which represent long-term WT operation and degradation as well as maintenance processes.
Modelling with limited/unavailable data	Simulation models are significantly dependent on the availability of input data such as failure and repair information which might be unavailable for some floating offshore wind turbines.	The PN technique is able model the degradation of systems by utilising Weibull distributions for time-to-failure characterisations, overcoming the concerns of limited/unavailable data.

Complexity of technique	The Bayesian network technique can become quite complex as there is the requirement to set conditional probability table (CPT) entries for each variable.	In the PN technique, the parameters which need to be set are the firing rates of timed transitions, which are equivalent to Weibull parameters.
Class imbalance problem	Data mining techniques applied to wind turbines commonly succumb to the class imbalance problem which is experienced as a result of one class of data (e.g., data in failure instances) being considerably less in quantity than another class of data (e.g., data in normal instances) This problem hinders the predictive capacity of data mining techniques.	As the PN technique does not require any meaningful amounts of WT condition monitoring data for analysis, it is immune to the class imbalance problem.

6.3 The proposed O&M planning model

6.3.1 The SPN based O&M planning model

Due to complex nature of the FOWTs and their support structures, we divided the system into eight subsystems including drivetrain unit, hydraulic system, brake system, yaw system, pitch system, rotor system, power system and structural components. These subsystems include a number of components, as listed in Table 6.2.

Table 6.2 FOWT Subsystems and Components

FOWT Subsystem	Component
Drivetrain	Main bearings
	Gearbox
	Main shafts
Hydraulic system	Gear pump
	Valves/pipes
Brake system	Callipers/pads
	Brake discs
Yaw system	Hydraulic actuator
	Bearing/gear
	Yaw brake

Pitch system	Hydraulic actuator
	Bearing/gear
Rotor system	Hub
	Blades
Power system	Generator
	Frequency converter
	Transformer
Structure	Tower
	Nacelle
	Mooring lines

The eight subsystems are considered to be connected in series with each other, meaning that the wind turbine cannot function if any of these components fails. The PN model of the overall system is represented in Figure 6.3. The primary aim of our model is to present the degradation process of each component. The maintenance strategy applied to FOWT system is CBM, and the maintenance is conducted when the condition of a sub-assembly reaches its degraded state. For the purpose of simplicity, the following assumptions are made:

- The CMS equipment are in a good working condition;
- The maintenance restores the condition of each sub-assembly to “normal” or “as good as new” state;
- Wind speed is within the necessary operating range of the wind turbine.

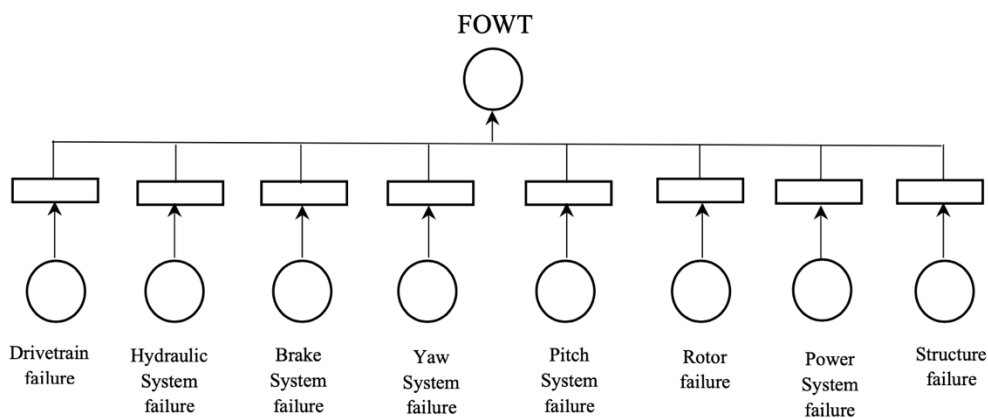


Figure 6.3 Petri net model for FOWT system failure

The software tool used to develop the SPN model for O&M planning of FOWTs is TimeNET Version 4 (Zimmermann and Knoke, 2007). TimeNET was designed by the Real-Time Systems and Robotics group at the Technische Universität Berlin, Germany, as an interface to model the SPNs with non-exponentially distributed firing times.

6.3.1.1 Modelling the degradation process

To model the degradation process of components, four states are defined: (i) normal state, (ii) degraded state, (iii) critical state, and (iv) functional failure state. The transitions linking these states represent events which take place for one state to progress into another, i.e., for the components to degrade from the normal to degraded to critical and finally to the functional failure state. The times associated with each transition represents how long it takes for the condition of the components to further progress. The model begins with the token residing in the *Normal* place. This signifies that the sub-assembly is operating as it normally should be. The presence of this token enables the transition *CO_1* (Continued Operation 1) to fire, transferring the token to the *Degraded* place after a delay represented by a Weibull distribution with parameters β and η . β represents the shape parameter and η represents the scale parameter (for this study, the scale parameter is represented in years). The movement of the token in this instance signifies the change in the asset's condition; therefore, the token being situated within the *Degraded* place signifies that the asset is in a degraded state.

As we assume that the resources (including transport vessels, service crew, spare parts and special tools) are available, the maintenance tasks begin immediately after when the condition of a component is identified as 'degraded'. In the case where resources might not be available for a maintenance task, the transition *CO_2* becomes enabled and fires, transferring the token from the *Degraded* place to the *Critical* place. The critical state in this model serves to notify the operators that functional failure will occur if no maintenance is performed. This process then continues until the token ends up in the *Failed* place. By default, this then prompts replacement of the component. The degradation process on TimeNET is shown in Figure 6.4.

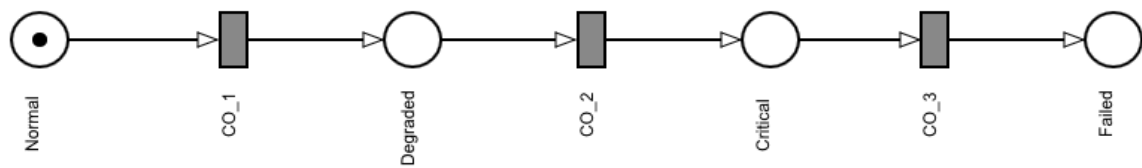


Figure 6.4 Degradation model on TimeNET

6.3.1.2 Modelling the condition monitoring system (CMS)

The CMS is utilised to continuously monitor and report the condition of FOWT components during operation. This process identifies and reveals any changes to the asset's condition based on pre-specified operational and performance metrics. Therefore, the CMS plays an extremely important role as the maintenance actions are taken based on alarm conditions. With the components working in normal condition (i.e., the token placed in the *Normal* place), any changes to the condition can be identified by the CMS. This will enable the aforementioned immediate transitions, moving the tokens into either the *normal*, *degraded*, *critical* or *failed* places. The positions of the tokens then reveal the known conditions of the components at that point in time. Thus, it is this condition of a component that determines if a maintenance action needs to be performed or not. The accuracy of the CMS is also important, as monitoring equipment like many other machines are prone to errors or faults. When there is an error in the CMS, the condition of components will be reported wrongly to operators, which may lead to either initiating a maintenance action when it is not needed or holding back a maintenance action when it is needed.

6.3.1.3 Modelling the maintenance process

The maintenance process includes several key stages including maintenance logistics, maintenance resource mobilization, actual repair/replacement, resource demobilization and end of maintenance activities. These stages are represented by the *Maint_Logistics*, *Mobilisation*, *At_FOWT*, *Demobilisation* and *End_Maint* states and are shown in Figure 6.5. The transitions linking these states represent the events which have to occur for the maintenance process to progress from one state to the next. The model has been set up such that each transition in this maintenance process can only become enabled if a token is

present in the place which precedes it. When it becomes enabled, the transition can only fire after a delay of time t . This delay is governed by the type of maintenance being performed on any particular component. Types of maintenance actions for wind turbines are explained in Table 6.3.

Table 6.3 Types of maintenance for wind turbines (Le and Andrews, 2016)

Maintenance Type	Description
Type 1	Heavy component, requires internal/external crane (>800-1000kg)
Type 2	Small parts, requires internal crane (<800-1000kg)
Type 3	Small parts, inside nacelle
Type 4	Small parts, outside nacelle

When the condition of a component reaches the *Degraded* state, the maintenance process begins, and the immediate transition *Start_Maint_Process* is fired. This transfers the token from the *Degraded* place and deposits it in the *Maint_Logistics* place. The transition *Logistics* is then enabled and fires only after a delay representing the logistics time has elapsed. The token is then deposited in the *Mobilization* place. As a result of this, the transition *Travel_to_FOWT* is enabled and fires only after a delay representing the travel time to the floating offshore wind farm. This then places the token in the *At_FOWT* place. This process continues until the maintenance process is completed with the token situated at the *End_Maint* place, enabling the transition *Back_to_Normal* which fires immediately. The token is finally deposited in the *Normal* place, signifying that the component has resumed normal operations.

The PN model, including the degradation process, maintenance process and condition monitoring process, for the FOWT system is shown in Figure 6.5.

6.4 Results and discussion

In this section, the proposed SPN model is applied to O&M planning of an NREL 5-MW spar buoy floating wind turbine system with an anticipated design lifetime of 25 years. The data for simulation of degradation and maintenance processes

of FOWT components was collected from the literature as well as wind energy industry databases. These data are given in the Appendix A. Table A.1 presents the types of maintenance actions adopted for the FOWT components. Table A.2 presents the Weibull distribution parameters for each stage of FOWT degradation. Table A.3 shows the parameters adopted for the maintenance of the FOWT based on each maintenance type. In Table A.2, it can be seen that the shape parameter (β) for each component remains greater than 1 (i.e., $\beta > 1$), meaning that the failure rate of each component consistently increases with time. In the context of this research, maintenance/repair is assumed to begin when the component reaches the “Degraded” state. After performing the maintenance, the component is assumed to get back to the ‘normal’ state or ‘as-good-as-new’, meaning that the time interval begins when the component starts operating and ends when the repair starts. The activities performed during repair/replacement process depend on the maintenance strategy adopted for that component. The simulation results are analysed to obtain other pertinent metrics such as the time to failure, expected number of repairs/interventions, and the repair/maintenance costs. These performance metrics for each component are then combined to determine the performance of the entire system.

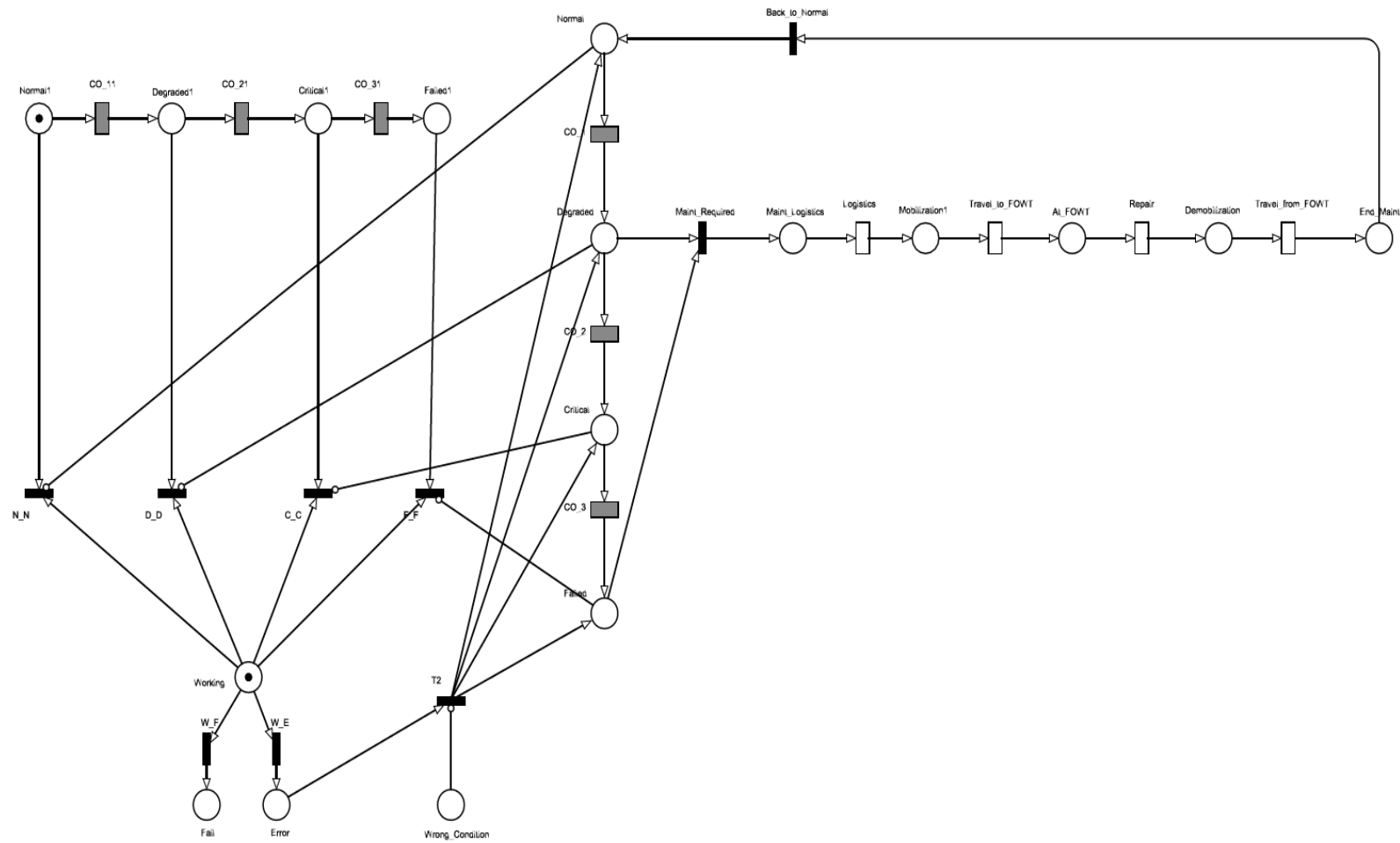
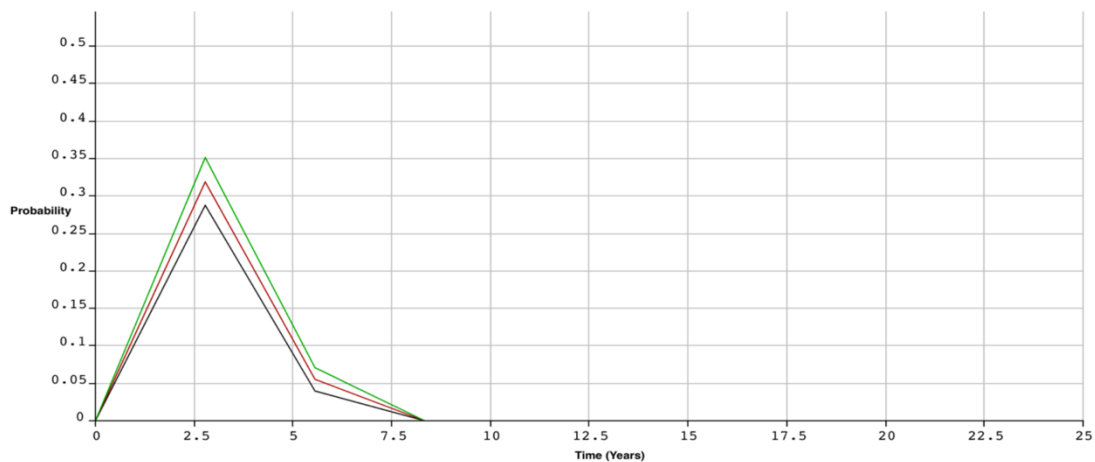


Figure 6.5 TimeNET model of component degradation and maintenance process for FOWT components

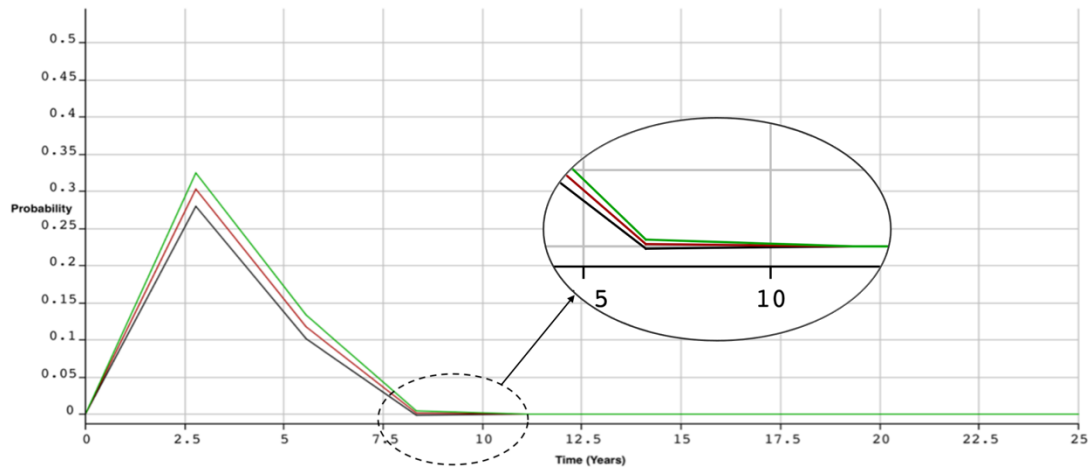
6.4.1 Component maintenance prediction

Given that maintenance is performed when CMS identifies the component condition as 'degraded', the time at which a repair must be initiated can be determined. By estimating the number of times each component reaches a degraded state over its lifetime, the total number of maintenance interventions can be calculated.

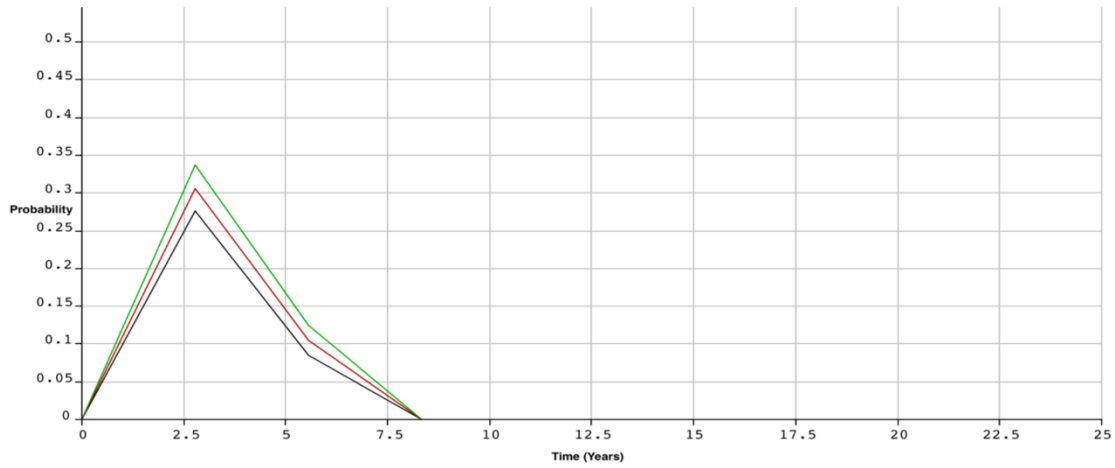
Taking the FOWT mooring system as an example, the simulation results in Figure 6.6 show that the three mooring lines reach a degraded state after 8.33 years, 11.11 years and 8.33 years, respectively with the y-axis representing the probability of the components being in the degraded state. The dominant failure mode of the mooring system is wear which becomes critical when it reaches a limit. This then triggers a maintenance which in this case is the *Type 4* maintenance, restoring the system to as-good-as-new or normal condition. It therefore follows that the three mooring lines will be repaired 3 times, 2.25 times and 3 times over 25-year lifetime, respectively. Table 6.4 shows the average length of time that it takes for each component of the FOWT system to reach a degraded state. This can then be used to predict the total number of maintenance activities which will need to be performed over the wind farm lifetime.



(a)



(b)



(c)

Figure 6.6 The performance of three mooring lines in a degraded state (a) line 1, (b) line 2, (c) line 3

6.4.2 Maintenance cost prediction

The cost of maintenance for each FOWT component depends on the type of maintenance adopted for that component. In this paper, four maintenance types as listed in Table 6.2 were considered. The costs associated with each type of maintenance include labour cost, material cost and logistics cost and have been obtained from Le and Andrews (2016). The total maintenance cost for each FOWT component is obtained by multiplying the cost of each maintenance by the expected number of maintenance actions performed on that component over the

wind farm lifetime. The expected number of repairs and associated costs for all FOWT components are given in Table 6.4.

Table 6.4 Expected number of repairs and associated costs

Subsystem	Component	Type of Maintenance	Cost of Repair Type (£)	Time to Degraded State (Years)	Expected Number of Repair	Cost of Repair (£)
Drivetrain	Bearing	3	10,000	8.33	3.00	30,000
	Gearbox	3	10,000	9.02	2.77	27,700
	Shaft	3	10,000	8.33	3.00	30,000
Hydraulic	Pump	2	41,000	12.50	2.00	82,000
	Valves/Pipes	3	6,000	6.25	4.00	24,000
Braking	Callipers/Pads	2	19,000	6.25	4.00	76,000
	Discs	2	19,000	5.25	4.76	90,440
Yaw	Actuator	3	12,000	5.25	4.76	57,120
	Bearing	3	10,000	8.39	2.98	29,800
	Brake	2	24,000	8.39	2.98	71,520
Pitch	Actuator	3	13,000	6.25	4.00	52,000
	Bearing	3	13,000	9.43	2.65	34,450
Rotor	Hub	3	8,000	9.43	2.65	21,200
	Blade	4	11,000	8.33	3.00	33,000
Power	Generator	2	65,000	9.43	2.65	172,250
	Converter	1	52,000	6.25	4.00	208,000
	Transformer	2	45,000	12.50	2.00	90000
Structure	Tower	4	27,000	12.50	2.00	54000
	Nacelle	4	12,000	8.33	3.00	36,000
	Mooring line 1	4	10,000	8.33	3.00	30,000
	Mooring line 2	4	10,000	11.11	2.25	22,500
	Mooring line 3	4	10,000	8.33	3.00	30,000
	Anchor	1	55,000	9.38	2.66	146,000

As can be seen in Table 6.4, the power converter is the most contributing component to the O&M cost of FOWTs, followed by structural components including anchors, mooring lines, tower and nacelle.

6.4.3 System downtime

The FOWT system experiences downtime when maintenance is performed. The downtime in this case is defined as the time between when the degradation is detected, and the repair task is completed. This encompasses the logistics time to prepare personnel, parts and equipment, time to travel to and from the FOWT and the actual repair time. It should be noted that the system downtime does not take into account the weather waiting time and the duration between the time when a degradation occurs, and it is detected. Weather waiting time is a function of the environmental conditions wherein the wind farm is situated. The downtime for each component is a function of the maintenance type.

Our results show, from the combination of the number of maintenance interventions in Table 6.4 and the duration of maintenance activities in Table A.3, that the highest system downtime (26.63 days) is attributed to the maintenance of the power converter, whereas the lowest system downtime (1.75 days) is attributed to the maintenance of the rotor blades, tower and nacelle. The average downtime caused by all components is estimated to be 5.65 days. This information can be used to determine the annual loss in energy production as a result of component degradation or failure.

6.4.4 Sensitivity analysis

A sensitivity analysis has been performed to understand the impact of CMS on system performance. In the proposed model, the CMS was assumed to be in perfect working condition. However, the CMS itself may experience downtime due to technical problems. In this study, the annual failure rate of the CMS is assumed to be 0.006. Table 6.5 shows the effect of the CMS failure rate on the mooring lines, power generator and yaw bearings. As can be seen, the probability of each component failing increases when the CMS failure rate is incorporated into the model. This implies that the condition of the CMS should also be a point of focus when planning O&M activities in floating offshore wind farms as it can affect the asset's operation.

Table 6.5 Probability of failure of gearbox, generator and yaw bearings under with CMS

Component	Probability of Component Failure	
	CMS in Perfect Condition	CMS with Failure Rate
Mooring line 1	0.449	0.695
Generator	0.438	0.679
Yaw bearings	0.467	0.685

6.5 Conclusion and future work

This paper has presented a stochastic Petri network (SPN) model for O&M planning of floating offshore wind turbines (FOWTs) and their support structures. The model encompassed the degradation processes, maintenance operations and condition monitoring system (CMS) for eight subassemblies of the floating offshore wind turbines. The expected number of failures in each component over its lifetime was predicted based on how often the component reaches its degraded state. The number and cost of maintenance interventions for each component as well as the entire system were predicted over the wind farm's lifetime with the yaw actuator and brake discs having the most expected number of repairs. However, the power converter was identified as the most expensive component to maintain when factoring the number of maintenance interventions and cost of each intervention.

The system downtime was also analysed, for all the different factors involved. The highest contributor to system downtime was determined to be the power converter, while the lowest contributors to downtime were the rotor blades, tower, nacelle and mooring lines. It was determined that maintenance effort should be focused on power converters as they were the most expensive component to maintain and caused the longest system downtime. Finally, a sensitivity analysis was performed to analyse the effect of the CMS on each component's performance. The analysis shows that the probability of failure of the component is lower with the CMS having higher reliability.

Further studies can be carried out on maintenance and degradation modelling of FOWTs using other advanced techniques such as Dynamic Bayesian Networks

and Markov processes. The model developed in this paper can be extended to take into account multiple FOWTs in offshore wind farms. Mooring lines can also be focused on in more detail with regards to O&M planning as its use in the wind energy industry is still relatively in its infancy. Lastly, the proposed model can also be applied towards O&M planning of other complex assets in both the onshore and offshore sectors.

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7 DEVELOPMENT OF A BAYESIAN NETWORK UPDATING MODEL FOR O&M PLANNING OF OFFSHORE WIND STRUCTURES

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Statement of contribution:

Tobiloba Elusakin was responsible for study conceptualisation, methodology, software, validation, formal analysis, investigation, data curation, writing - original draft, review and editing, visualisation and project administration. Dr Mahmoud Shafiee was responsible for formal analysis, investigation, review and editing, visualisation and supervision. Tosin Adedipe was responsible for review and editing.

Abstract

Offshore wind structures are generally more complex than their onshore counterparts due to requirements to overcome challenges associated with severe marine environments and impact under substantial wave loading. There are difficulties associated with the accurate analysis for fatigue damage in offshore wind structures as a result of uncertainty within the crack growth models and to overcome this, a method called Bayesian updating has been investigated. The objective of this study is to propose a model for predicting fatigue crack growth based on real-time hourly observations from remote condition monitoring sensors. Bayesian updating, is applied to the Paris law, which can be used to represent the growth of fatigue-induced cracks in structures. The research method employed in this study also involves the use of influence diagrams to show the effects of condition monitoring decisions on fatigue crack growth. The model developed has been applied to predict fatigue crack growth in an offshore wind turbine monopile over a 24-hour period; the results show that real-time condition monitoring can be used to predict fatigue crack growth in offshore wind turbine monopiles.

7.1 Introduction

Wind energy installations have become increasingly more popular over the past decade. In the last ten years, Europe's installed capacity has increased by 144%, from 84 GW in 2010 to 205 GW in 2020 (European Wind Energy Association, 2012; Wind Europe, 2020). With the desire for more available space and higher wind speeds, the wind industry is gradually moving more towards offshore environments, which present new operational scenarios. These new scenarios provide new challenges to operation and maintenance (O&M) planners as a result of rapidly changing weather conditions, differences in system dynamics, condition monitoring, resource logistics, availability and accessibility constraints for deepwater wind farm sites (Kang *et al.*, 2019).

O&M has been recognised as one of the critical cost-driving activities throughout the life cycle of wind farms both onshore and offshore, accounting for about 15-30% of the levelized cost of energy (LCOE) (Oelker *et al.*, 2011; Shafiee and Sørensen, 2017; Kang *et al.*, 2019). To reduce the O&M costs and, by extension, the LCOE for wind turbines while improving their availability, the tools and techniques employed must be improved. O&M planning and decision-making, being dynamic processes, should be optimised to take into account new information obtained via inspections or condition monitoring (Soliman and Frangopol, 2014; Decò and Frangopol, 2015). As most modern wind turbine systems have been equipped with condition monitoring systems (CMS) or supervisory control and data acquisition systems (SCADA) systems (Nielsen and Sørensen, 2010b), prediction of system reliability and performance has become of paramount importance.

In structural systems, both the Paris law and the Palmgren-Miner's damage accumulation law can be used for fatigue assessment. Paris' law, which represents the modelling of fatigue crack growth based on fracture mechanics is preferred to Palmgren-Miner's damage accumulation law due to the latter not being able to account for measurable damage size (Ziegler, 2018). The use of the Paris law has been seen to be a common theme in modelling the progression of fatigue-based crack growth in structures while incorporating information from

inspection and condition monitoring (Straub, 2009a; Nielsen and Sørensen, 2010b; Zárate, *et al.*, 2012a, 2012b; Stutzmann *et al.*, 2017; Yang and Frangopol, 2017;). These studies all focused on deteriorating components and establishing damage models which are based on fracture mechanics. Offshore wind turbines are perpetually exposed to cyclic loading, hence the design of OWT monopiles is driven by fatigue limit state, emphasising the importance of investigations into fatigue-based deterioration (Velarde and Bachynski, 2017; Njomo-Wandji *et al.*, 2019). The fatigue life of an OWT component encompasses three stages: crack initiation, crack propagation and component failure. Due to the monopile being a welded steel structure, most of its fatigue life is spent in the crack propagation stage (Ziegler, 2018).

Investigations into fatigue-based deterioration can be done using the Bayesian network (BN) technique. The BN technique is very flexible in that it allows for the use of both objective and subjective inputs in the network and can allow updating based on new information (Langseth and Portinale, 2006; Kougioumtzoglou and Lazakis, 2015; Lazakis and Kougioumtzoglou, 2019). The network is complex as the number of input variables and the interdependent relationships have to be quantified in conditional probability tables (CPT). In wind energy applications, BNs have been used for wind turbine state condition or estimation, fault diagnosis, deterioration modelling, parameter forecasting, reliability assessment and operation and maintenance planning (Adedipe *et al.*, 2020). Extreme responses of offshore wind turbines have been analysed by Cheng *et al.*, (2002) and Lee *et al.*, (2013) using Bayesian analysis and Bayesian spline methods respectively. O&M planning in wind energy is very important as it helps to reduce costs throughout the lifecycle of a windfarm. Bayesian network approximations such as Bayesian decision theory and dynamic Bayesian networks (DBN) have been applied in O&M planning for offshore wind turbines (Nielsen and Sørensen, 2010).

There have been previous studies conducted on Bayesian model updating of fatigue crack growth in offshore structures. However, these studies do not take into account real-time condition monitoring information while modelling

degradation and predicting crack growth. There are also a limited number of studies which focus on the monopile despite it being the most commonly used foundation for fixed-bottom OWTs. In this paper, a model for updating and predicting fatigue crack length based on real-time condition monitoring information is proposed using dynamic BNs and influence diagrams. This study differs from previous studies in that it proposes the incorporation of real-time condition monitoring information to update fatigue crack size information for OWT monopiles, rather than measurements from planned inspections. This is especially important for offshore wind turbine monopiles as they are a critical part of the offshore wind turbine.

The organisation of the paper is as follows: section 7.2 contains an overview of literature on O&M planning of offshore wind turbines, section 7.3 discusses the BN technique as well as the model developed for this study, section 7.4 presents the results and analysis, and section 7.5 concludes the study and discusses opportunities for further studies.

7.2 O&M planning of offshore wind turbines

Several techniques can be applied to O&M planning of structural systems. Shafiee and Sørensen, (2017) discussed a number of tools and techniques which are categorised as qualitative or quantitative techniques. These include stochastic models, Markov models, Petri net models, analytical models, Bayesian network (BN) models and fuzzy models. Among these techniques, the BN technique has been identified as a valuable tool for fault diagnosis and prognosis as well as maintenance planning optimisation for deteriorating systems (Friis-Hansen, 2001; Straub, 2009; Nielsen and Sørensen, 2010). One primary reason for this is the model's ability to be updated when new information is available – i.e., with new information from condition monitoring systems or inspection reports (Langseth and Portinale, 2006; Jensen and Nielsen, 2007, Kougiumtzoglou and Lazakis, 2015; Lazakis and Kougiumtzoglou, 2019). The Bayesian decision theory is also especially useful when uncertainty is present and there is limited information about the system being modelled or monitored. Uncertainty in the system may arise from environmental uncertainties (wind and wave loading),

material strength properties, degradation variables and model uncertainties (DNVGL, 2015).

In order to model the system reliability and deterioration, predictive models are invaluable and a probabilistic approach like Bayesian networks is especially ideal for stochastic variable considerations. Bayesian networks can be developed to model system behaviours of a wind farm cluster using discrete or continuous variables in order to predict the reliability outcomes of the systems for better O&M decision-making. Bayesian inference is a terminology used to describe the process of using Bayesian statistics to estimate the posterior probability distribution of variables based on evidence or observations (Garbatov and Soares, 2002). Based on the data collected for the different variables considered, the Bayesian network can therefore be constructed, and the conditional probability distributions (CPD) estimated. Whenever a new observation is introduced into the network, such as inspection or condition monitoring information, this will update the conditional probabilities of the system (Li and Mahadevan, 2017).

Bayesian networks aid in degradation modelling even when some parameters are unknown, and quantities are unobservable (Friis-Hansen, 2001). In this case, expert knowledge is used to bridge the gap. With respect to the application of BN toward modelling the deterioration of offshore wind structures, a number of studies have been conducted. Nielsen and Sorensen, (2017) performed a study in which the BN technique was used to incorporate updates from data obtained from the inspection of wind turbine blades to determine the remaining useful life (RUL). Prior to this, Nielsen and Sørensen, (2010a) applied limited information influence diagrams (LIMID), an (extension) of BN toward risk-based O&M planning of offshore wind turbine structures. Nielsen and Sørensen (2010b) also used DBN to model the propagation of fatigue-based cracks in the main bearing of an offshore wind turbine. In this study, the probabilities of failure of the bearing with and without monitoring were determined to assist in decision-support for repair and maintenance actions.

Structural components of offshore wind turbines experience considerable fatigue damage over their operational lifecycles and the prediction of this fatigue damage presents significant uncertainties (Nielsen and Sørensen, 2011). In order to deal with uncertainties in fatigue damage measurements, a number of inspection techniques have been developed to detect and measure fatigue damage in OWT structural components during their operational service life. These techniques include ultrasonic testing (UT), magnetic particle inspection (MPI), Alternating Current Field Measurement (ACFM), and Eddy Current (EC) (DNVGL, 2015; Ziegler, 2018). For continuous crack propagation monitoring, the only viable techniques are identified as acoustic emission and the Strainstall CrackFirst™ system (Kolios *et al.*, 2018).

In offshore wind turbine monopiles, fatigue crack growth analysis has been the subject of a surprisingly limited number of studies. Mehmanparast *et al.* (2017) investigated the initiation and propagation of fatigue cracks in OWT monopile weldments with fatigue crack growth tests in air and sea water environments. Ziegler *et al.* (2016) investigated the effect of load sequencing on fatigue crack growth, developing a simplified crack propagation model based on Paris' law. In Stutzmann *et al.* (2017) crack size distributions in OWT monopiles were simulated and updated using Bayesian Networks with information from inspections. With the prevalence of monopile supported offshore wind turbines, more studies on fatigue-based crack propagation are necessary.

7.3 Methodology

7.3.1 Bayesian belief updating

In the context of fatigue crack degradation modelling, Bayesian updating or inferencing involves the update of input parameters of the degradation model to optimise future predictions (Rocher *et al.*, 2014). It is used to determine the posterior belief about an event after observing evidence. Using the Bayes rule, information gained through inspection can be combined with a prior prediction about crack size distribution to obtain an updated posterior distribution for the crack size.

From equation (7-1), assuming variable B is observed to exist in a state b_j and B causes A to occur. By applying the Bayes rule to each state of A , the probability distribution $P(A|B = b_j)$ can be calculated as follows:

$$P(A|B = b_j) = \frac{P(B = b_j|A) \times P(A)}{\sum_{all\ i} P(B = b_j|A = a_i) P(A = a_i)} \quad (7-1)$$

Performing Bayesian updating in this way only works if the network being addressed is quite small. If the network is large, there are a few problems that arise, chief of which is ensuring consistency in updating nodes along with evidence and performing efficient inferencing (Friis-Hansen, 2001).

7.3.2 Fatigue crack growth modelling

The process of identifying and quantifying damage through the combination of detection algorithms and condition monitoring systems in engineering structures is known as structural health monitoring (SHM). In wind turbine structures, SHM enables fatigue-damage to be monitored and diagnosed (Karandikar *et al.*, 2012). Fatigue damage assessment can generally be done using two methods: fatigue-based crack growth modelling and S-N curves based on Miner's damage accumulation principle. The former is applied in this study as it is more suitable for planning of maintenance intervention for structures (Yang and Frangopol, 2017).

Fatigue-based crack growth is accurately predicted using the Paris-Edrogon equation, more commonly known as the Paris law, which defines the relationship between the rate of increase of crack length per load cycle and the stress intensity factor range (Paris and Erdogan, 1963):

$$\frac{da}{dN} = C(\Delta K)^m \quad (7-2)$$

Where a is the crack length, N is the number of load cycles, C and m are material model parameters for fatigue crack growth and ΔK is the stress intensity factor range related to the loading amplitude. ΔK itself can be calculated as a function

of the stress range, geometry constant, and crack length as seen in the equation below (Yang and Frangopol, 2017):

$$\Delta K = S_{re} G \sqrt{\pi a} \quad (7-3)$$

Where S_{re} represents the stress range and G represents the geometry constant related to the crack length. For this study, a geometry constant of 1.0, based on recommendations for fatigue analysis of crack growth by DNVGL (2015), will be used. Based on equations (7-2) and (7-3), the crack size at time t (i.e., a_t) can be estimated in the following equation:

$$a_t = \left[\left(1 - \frac{m}{2} \right) C \Delta S^m \pi^{m/2} \Delta N + a_{t-1}^{(1-m/2)} \right]^{(1-m/2)^{-1}} \quad (7-4)$$

Where a_t is crack size at time t , ΔN is the number of stress cycles during a time step, a_0 is the initial crack size, and ΔS represents the stress range. Structural failure is expected to occur when crack length reaches a critical point, a_c .

7.3.3 DBN modelling process

The model developed for this study was created using the commercially available software Netica Application (Norsys Software Corporation, 2019). It has an easy-to-use graphical user interface (GUI) which can be used to create and work with Bayesian belief networks and influence diagrams as well as relationships between different variables which can be inputted manually in the form of individual probability values, equations and data files.

The BN model developed in this study proposes the real-time prediction of fatigue crack growth based on observations from condition monitoring systems (CMS) which provides a continuous stream of information (once every hour). The BN model is extended into an influence diagram (ID) to model the decision to perform condition monitoring. Due to the lack of data concerning the existence and use of remote condition monitoring sensors to measure fatigue crack growth on OWT monopiles, this study has applied the probability of detection (PoD) parameters for non-destructive testing (NDT) techniques which are normally found from the inspection of fatigue cracks in offshore wind structures. The PoD for NDT

inspection techniques is calculated using the equation given below (DNVGL, 2015):

$$PoD(a) = 1 - \left[\frac{1}{1 + \left(\frac{a}{X_0} \right)^b} \right] \quad (7-5)$$

Where a represents crack size in mm and b and X_0 are the distribution parameters which depend on the chosen NDT technique.

For ease of computation and for the purposes of this model, a number of assumptions have been made:

- The Ultrasonic Testing (UT) technique has been assumed as the condition monitoring technique for this study.
- The CMS provides information on crack size every hour
- The crack length does not reach a point of criticality

Based on the fatigue crack growth model in equation (7-4), a Bayesian network model of the system within a 24-hour time period has been developed with 24 time slices (T) which represent hourly crack measurement updates from the condition monitoring system. A simple DBN model of fatigue-based crack growth can be seen in Figure 7.1.

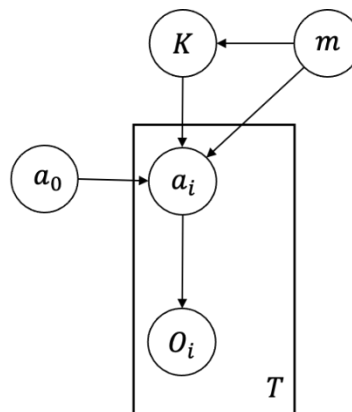


Figure 7.1 Simple representation of Fatigue crack growth model

These time points are represented as nature nodes within the Netica graphical user interface and are shown as the child nodes $a_1, a_2, \dots, a_{24}$. The node O_i is connected as a child node of a_i and represents observations from the CMS. This node possesses the same states as a_i plus a state of “no detection” to account for the scenario in which the crack size is too small to be detected. Connected to the node a_i as parent nodes are the material parameter m and variable K as these variables represent constants in the model regardless of the number of time steps being modelled. The variable K in this model is an intermediate node representing the amalgamation of the material parameter C and stress range ΔS . This amalgamation process is done to reduce the computational load and is referred to as “divorcing” (Straub and Der Kiureghian, 2010). This is given by the following equation:

$$K = C \cdot \Delta S^m \cdot \pi^{m/2} \quad (7-6)$$

The discretisation of continuous nodes a_0, m, K and a_i is performed based on processes summarised in Yang and Frangopol, (2017). The continuous nodes are discretised into bins in order to reduce the size of the Markov envelopes created from the aggregation of all the variables. The nodes with known statistical distributions (m and a_0) are discretised into 10 bins with minimum and maximum edges represented as $\mu - 3\sigma$ and $\mu + 3\sigma$ respectively. The nodes with unknown distributions (K and a_i) are also discretised into 10 bins with minimum and maximum edges represented as percentile values of Monte Carlo samples – 5th and 95th percentiles for K and a_i .

7.3.4 Influence diagram

In order to model the application of the condition monitoring system (CMS), the dynamic Bayesian network model is extended to an influence diagram (ID) through the addition of decision and utility nodes. In an ID, random variables are represented as chance nodes and each decision node contains multiple decision options which can affect chance nodes and incur costs. These costs represented by the utility nodes (Jensen and Nielsen, 2007). From Figure 7.2, the node D_{CMS} represents a decision node with two alternatives from which to choose: no CMS,

and Ultrasonic Testing (UT). This node has been incorporated at each time slice to exhibit the decision support and is connected to the observation node O_i which represents the measurements from the condition monitoring system. The observation node is also connected to the crack size node (a_i) and contains all the same states plus a state of “no detection” to account for the scenario in which the crack size is too small to be detected. With this model being a snapshot of fatigue crack growth in a full day of observations, the critical crack length a_{cr} is not taken into account in analysis. Based on equation (7-5), the probability of detection distribution parameters for UT are $b = 0.642$ and $X_0 = 0.410$ as provided by DNVGL (2015).

Figure 7.2 shows a simple representation of the Bayesian network for fatigue crack growth modelling in this study.

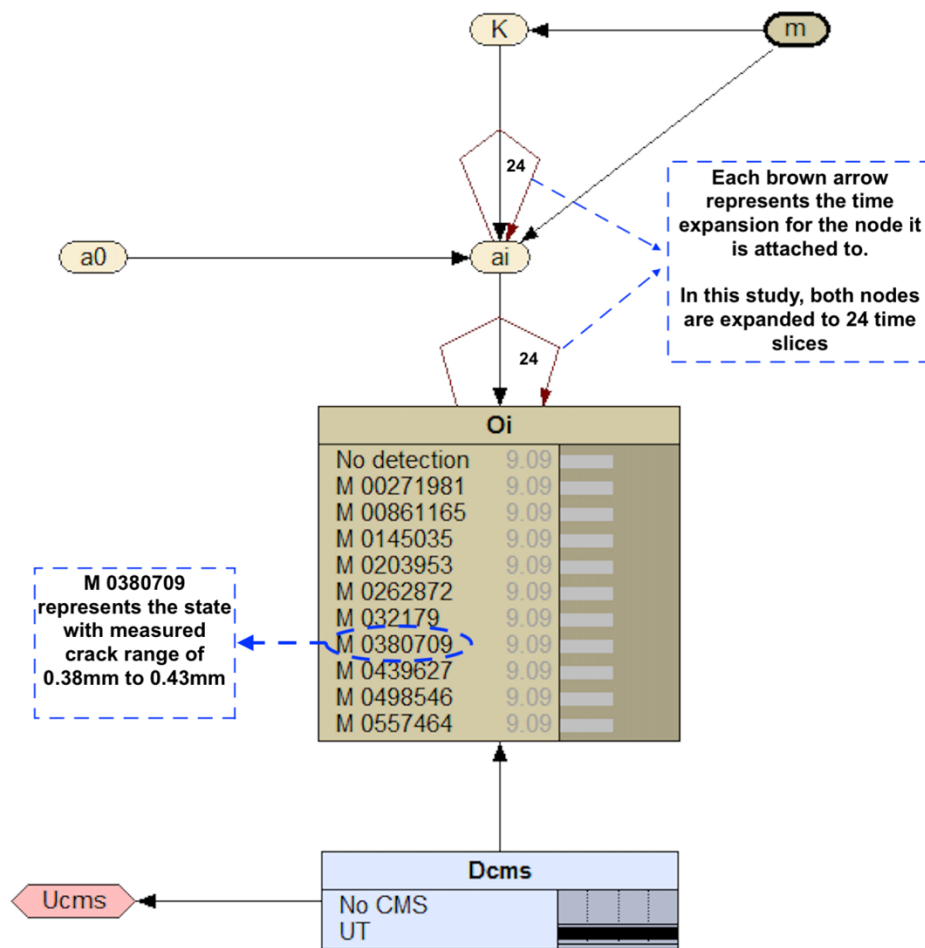


Figure 7.2 Simple representation of the fatigue crack growth influence diagram in Netica

7.3.5 OWT monopile case study

The monopile considered in this study was taken from a generic offshore wind turbine used in phase I of the Offshore Code Comparison Collaboration (OC3) project. The monopile supports a NREL 5MW reference turbine and is located in water with a depth of 20m (Jonkman & Musial, 2010). Fatigue-based crack propagation has been modelled using equation (7-3) with uncertainties taken account of through the random variables (as shown in Table 7.1).

Table 7.1 Variables in stochastic crack growth model (Nielsen and Sørensen, 2010; Ziegler *et al.*, 2016; Stutzmann *et al.*, 2017)

Variable	Mean	Standard Deviation	Distribution
Initial crack size, a_0 (mm)	0.5	0.05	Exponential
Crack growth model constant, m	3.0	0.15	Normal
Crack growth model constant, C	3.322×10^{-13}	1.660×10^{-13}	Normal
Stress range, S_{re} (MPa or Nmm ⁻²)	60	10	Normal
Number of cycles, N (cycles/hr)	1.14×10^2	-	Deterministic
Geometric parameter (G)	1	-	Deterministic

7.4 Analysis and discussion

The fatigue crack growth over time can be seen in Figure 7.3. Given the short period of time being observed for this study (24 hours), it is essential to note that the extent of degradation observed in the model developed is near infinitesimal. However, it can be inferred from the model how crack growth can be predicted given real-time observations obtained from with remote condition monitoring systems.

As an example, assuming a crack length measurement within a range of 0.38mm to 0.43mm was made with the first observation (i.e., at state M 0380709 in node O_1 shown in Figure 7.2), the crack growth going forward can be predicted. From the model, it was deduced that the crack length would remain within the range of 0.38mm to 0.43mm after 24 hours, meaning crack length would remain within the state M 0380709 in the node O_1 . This is due to this state having the highest probability of 0.320 as seen in Figure 7.3. This probability was observed to remain constant over the 24-hour time period. It is important to note here that, if crack growth is modelled over a longer period of time, then it is likely that there will be a bigger change in the probabilities of occurrence for different crack sizes.

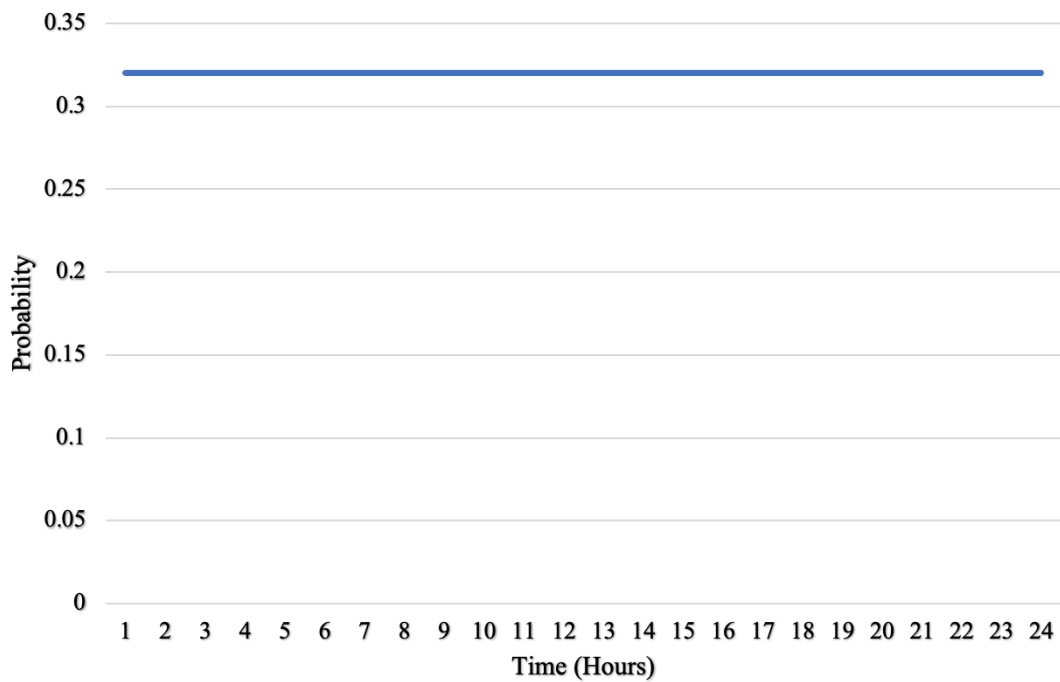


Figure 7.3 Probability of fatigue crack length being in the state M 0380709 (0.38mm-0.43mm) as a function of time

The fatigue crack growth can also be predicted given an assumption of crack length measurement within a range of 0.38mm and 0.43mm at other time slices. For instance, if a measurement is made after the 12th hour (i.e., at O_{12}), then from the crack growth model it can be seen that the crack length remains within the state M 0380709 (0.38mm to 0.43mm) from the 13th to the 24th hours (O_{13} to O_{24}) as a result of having the highest probability of 0.323 which remains constant. The increase in probability from 0.320 to 0.323 is seen as evidence of model validity as a measurement made at a later time slice is more likely to predict future crack growth than a measurement made at an earlier time slice.

7.5 Conclusion and further works

This study has looked into the use of Bayesian updating in fatigue crack growth modelling for offshore wind turbine monopiles. The model, which is based on Paris' law, predicts the deterioration of an OWT monopile as a result of fatigue crack growth over a 24-hour period and updates the crack length on an hourly

basis based on observations from a hypothetical condition monitoring system. Due to the lack of existing workable technology and available data on continuous fatigue crack monitoring in OWT monopiles, this study has used the ultrasonic testing (UT) inspection technique as the CMS. Analyses performed determined that updating the crack size based on near real-time observations is possible up to a point but would require excessive computing power to model hourly observations in order to predict crack growth over the operational lifetime of the OWT monopile.

Future work and research can be geared towards modelling more granular crack length observations (for example, every 10 minutes) as well as extending the model to cover the entire lifetime of the OWT monopile. The model developed can also be expanded to accommodate the input of more evidence and allow for the effect of more decisions on monitoring and repair to be identified and analysed. Lastly, further work can be done to demonstrate how the model developed can be combined with a decision model for life extension of offshore assets.

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8 OVERALL DISCUSSIONS

The increasing complexities associated with operating in the offshore environment and the growing adoption of CBM has necessitated the development of advanced models for reliability analysis. Advanced techniques such as Petri nets (PNs) and Bayesian networks (BNs) have been demonstrated to be adept at modelling these complexities and incorporating both degradation and CBM into offshore energy systems. The overall aim of the research was to develop advanced reliability analytics for the analysis of critical offshore energy assets operating in dynamic conditions and under condition-based maintenance regime in order to improve overall reliability as well as operation and maintenance.

In this chapter, an overall discussion of the results in this thesis is presented, with the specific contributions of the thesis summarised. This is done by demonstrating that the results from each publication (chapters 2-7) can be connected in a logical thought process, exhibiting coherence with the overall thesis aim. The contributions of this thesis have been summarised according to each publication.

8.1 Linking the results

The first objective of this thesis was achieved through extensive literature reviews which focused on existing research on the reliability of the subsea BOPs and offshore wind turbines, as well as reliability analysis techniques which have been applied to both assets. To achieve this objective, a systematic literature review process was applied, in which a wide-ranging and transparent search was conducted across different research databases, enabling replicability while diminishing bias. The findings from the review of the subsea BOP touched on the benefits accrued from the critical assessment of identified design, operation and maintenance challenges, the effect of the Macondo disaster on the safety of subsea BOPs, the levels of susceptibility of the different BOP subsystems to failure, and the advantages of advanced reliability analysis techniques over their conventional counterparts. These findings can provide offshore oil and gas stakeholders with valuable insights into identifying the design, deployment and

operational issues which require attention, particularly with movement into more uncharted exploratory conditions. For the offshore wind turbine, the literature review revealed unsurprisingly that OWT structural components have been most popular with respect to reliability analysis and the technique most employed was found to be the first order reliability method (FORM), followed by the FMEA and FTA techniques respectively.

The second objective of this thesis, which was to develop a framework for the effective and efficient implementation of CBM in offshore assets, was achieved through chapter 3, in which a framework based on the V-model architecture was developed followed by an economic feasibility analysis of CBM implementation. This research was conducted to address the lack of solutions geared towards CBM use in offshore energy production systems. Firstly, an established 'systems engineering' approach called the V-model methodology was applied to identify system requirements and develop a resulting framework. The first step in this framework, which is to conduct a feasibility analysis of CBM implementation, was then elaborated on. In this analysis, the NPV and BCR techniques were applied to take into account the costs and benefits of CBM implementation. The applicability of the proposed method was verified using the NOV Rigsentry® condition monitoring system case study. The proposed approach will benefit asset managers and operators by providing a key decision-making tool with which a strong financial case for implementing CBM can be made.

The third objective of this thesis was to develop analytical reliability models for offshore energy assets operating under CBM. This objective was achieved through chapters 4 and 5, where two different advanced techniques, SPN and DBN, were applied to analyse the reliability of a subsea BOP and an OWT gearbox respectively. First, a variation of the PN technique, the stochastic PN, was used to analyse the reliability of the subsea BOP. The SPN technique was applied here because of its ability to take into account the temporal nature of the subsea BOP operation and incorporate the CBM regime. The five BOP subsystems were divided into two categories: degrading and binary units. The results of this study indicated that the reliability and MTBF of complex offshore

energy systems can be improved through the incorporation of CBM as the preeminent maintenance policy and the application of redundancy. The SPN model developed in this study can help offshore oil and gas practitioners to address the problem of reliability allocation, allowing for more targeted focus based on the criticality of offshore production systems. This model can also help offshore oil and gas practitioners more accurately represent the realistic operational conditions in which offshore energy assets operate. The successful development of the SPN model which incorporated degradation and CBM led to an endeavour to perform reliability analysis using a different advanced technique on an offshore renewable energy asset. Furthermore, literature review conducted on the reliability analysis of offshore wind turbines in chapter 5 revealed that research on the application of the BN technique on OWTs was severely lacking. Therefore, in chapter 5, the reliability of an OWT gearbox was analysed and fault diagnosis performed using the DBN technique. The model developed and proposed incorporates degradation and CBM information for all the gearbox subassemblies to perform reliability analyses as well as fault diagnoses. Results from this study demonstrated that the DBN technique can also be used to perform reliability analysis while incorporating CBM. The DBN model can be applied by offshore wind industry practitioners for more accurate reliability allocation in addition to fault diagnosis in complex mechanical systems. This model will also provide researchers a basis on which reliability analysis can be done while considering CBM.

Next, the fourth objective of this thesis was to develop integrated models for optimising the operability and maintainability of offshore energy assets based on techniques applied in chapters 4 and 5. This objective was achieved through chapters 6 and 7. In chapter 6, the SPN technique was applied toward optimising the operation and maintenance of a floating offshore wind turbine. The model developed incorporated all the interrelationships between the different factors which influence the O&M planning of FOWTs, including deterioration, renewal, and condition monitoring for the eight system subassemblies. Results from this study demonstrated the versatility of the PN technique by exhibiting its capabilities for O&M optimisation of complex offshore energy systems. This SPN

model will be an especially useful tool for offshore wind asset managers in planning the O&M of complex assets at any point in the asset's operation, while taking into account the maintenance strategy. In chapter 7, the BN technique was used for O&M planning through the development of a BN updating model. In this study, a model for predicting fatigue-based crack growth was developed and proposed based on continuous real-time hourly observations from remote condition monitoring systems, which is a novel concept. The model developed in this study can be used as a springboard upon which fatigue crack growth over the operational lifetime of offshore structures can be modelled and predicted given real-time condition monitoring information.

The fifth objective of this thesis was to evaluate the developed asset reliability and O&M models against benchmark industrial case studies in offshore oil and gas and offshore wind energy. This objective was an essential part of this thesis and was achieved through chapters 4-7. In chapter 4, the SPN model developed for reliability analysis was evaluated against a subsea BOP. The five subsystems of the subsea BOP were divided into two categories: degrading and binary units. The reliability, availability and MTBF of the BOP system were determined while taking into consideration the degradation and CBM regime. The reliability importance and failure criticality index for each subsystem were also determined. Sensitivity analyses were then performed to evaluate the effects of CBM implementation and redundancy on the system performance. The results from this analysis show reasonable agreement with the literature in relation to the criticality of each BOP subsystem. In chapter 5, a DBN model developed for advanced reliability analysis and fault diagnosis of an OWT gearbox. Standard dependability metrics such as the reliability, availability and MTBF for each subassembly as well as the entire gearbox system were determined. Advanced reliability metrics such as failure criticality index and reliability importance were also obtained for each gearbox subassembly. Sensitivity analysis was performed to demonstrate the effect of CBM and redundancy on the reliability analysis and fault diagnosis, showing that the incorporation of CBM and redundancy do improve reliability. In chapter 6, an SPN model was applied again, this time toward the O&M planning of a FOWT. The number of maintenance interventions,

cost of maintenance and amount of system downtime were obtained for each subassembly as well as the entire NREL 5-MW spar buoy FOWT system. The results of this study highlighted the power converter as the highest contributor to system downtime and where maintenance efforts should be mainly focused on. The study also demonstrated the effect of employing CBM, as the probability of failure of the FOWT subassemblies were determined to be lower with the inclusion of a working condition monitoring system. In chapter 7, the DBN model was again applied toward modelling fatigue crack growth in an OWT monopile over a 24-hour period. The results of this study demonstrated that updating crack size based on regular condition monitoring observations is possible. However, in order to model real-time observations over the 25-year operational lifetime of the OWT monopile, excessive computing power would be required.

8.2 Comparing reliability analysis techniques

With regard to the reliability analyses conducted in this thesis, key similarities and differences were identified between the DBN and SPN techniques. The first similarity identified is that both techniques possess the capacity to take into account the change in an asset's condition over time. Additionally, both techniques were found to be able to incorporate repairability into the models developed, meaning a system is not just assumed to fail once over its operational lifetime. These similarities are exhibited in the models developed in chapters 4-7.

In terms of differences, the DBN technique was deduced to possess the ability to perform better diagnostic analysis, i.e., determine the root cause of failure as seen in chapter 5. It was also found to possess the ability to incorporate new evidence even after the model has been built in order to update prior beliefs and obtain new beliefs regarding the probabilities of failure. In addition to this, DBN was found to be able to support decision-making through the incorporation of decision and utility nodes into the model, as seen in chapters 5 and 7. The DBN technique is also able to determine the posterior probability for an event given new evidence, which is something that cannot be done using the SPN technique. However, SPN was found to be more user-friendly than DBN. This is as a result

of the complexity associated with setting the parameters for both models. In SPN, the only parameters that needed to be set were the firing rates of timed transitions. With DBN on the other hand, the conditional probability tables (CPTs), which represent all possible combinations of values of parent and child nodes, needed to be obtained for each variable in order to develop a functioning model. This can present a challenge for non-experts who do not have extensive knowledge of the system.

The capabilities and drawbacks of the most common reliability analysis techniques can be seen in Table 8.1.

Table 8.1 Capabilities and limitations of the most common reliability analysis methods

Technique	Capabilities	Limitations
Petri Nets	<ul style="list-style-type: none"> - Ideal for time-variant and time-invariant system analysis. - Can be used to evaluate different kinds of mechanical, electrical or structural systems. - Possesses a graphical component, aiding visual communication. - Analogous to continuous-time Markov chain. - Possesses the ability to incorporate maintenance into reliability analysis. - Can be used as a standalone technique or be combined with other reliability analysis techniques. - Can develop both discrete and continuous models of time. 	<ul style="list-style-type: none"> - PN models are susceptible to the state-space explosion problem-leading to difficulty in developing models for complex industrial processes. - PN technique is unable to improve its diagnostic prowess over time. - Experts require extensive system knowledge to accurately model system behaviour.
Bayesian Network	<ul style="list-style-type: none"> - Ideal for both time-variant and time-invariant analysis. - Can perform both forward (prognostic) and backward (diagnostic) analysis. - Possesses the ability to incorporate maintenance into reliability analysis. 	<ul style="list-style-type: none"> - No set guidelines for developing networks for a system, meaning that different models which give the same result can be created for the same system. - There is the risk of unnecessary model complexities when parent-child relationships are not properly defined.

	<ul style="list-style-type: none"> - Are useful for both dynamic risk assessment and reliability assessment. - Can overcome the state-space explosion problem. - BN provides the ability to learn using machine learning techniques with training data. - Can develop both discrete and continuous models of time. - Can be applied as a standalone technique or in conjunction with other techniques. 	<ul style="list-style-type: none"> - Experts require extensive system knowledge to accurately model system behaviour.
FTA	<ul style="list-style-type: none"> - Connections between faults and causes are represented graphically - Possesses a number of extensions such as component, dynamic and fuzzy fault trees. 	<ul style="list-style-type: none"> - Classical fault trees are incapable of model dynamic scenarios. - The analysis presents an overly simplistic representation of system failure. - Incapable of capturing sequence-dependent behaviour. - Primarily a manual process. - Cannot incorporate continuous distributions. - Cannot incorporate repairability.
FMEA	<ul style="list-style-type: none"> - Contains both quantitative and qualitative analysis. - Can be used to identify failures early in the design process. 	<ul style="list-style-type: none"> - Risk priority number is not informative enough for practitioners in relation to criticality. - Can only be done as a manual process. - Analysis is only as good as the people behind them.
RBD	<ul style="list-style-type: none"> - Can model the relationship between components through either series or parallel configurations or a combination of both. 	<ul style="list-style-type: none"> - Suited to predominantly non-repairable systems.
Markov Models	<ul style="list-style-type: none"> - Known to be flexible. - Uniquely suitable for assessment of redundant systems. - Widely used for modelling complex systems with multiple degradation states. 	<ul style="list-style-type: none"> - Can be tedious to determine rates due to lack of data. - It is possible for some states and transitions to be lost when defining both elements for complex systems. - Susceptible to the state space explosion problem. - Inappropriate for modelling short time intervals.

	<ul style="list-style-type: none"> - Deterioration can be modelled using discrete or continuous Markov model. - Can be incorporated with other classical reliability analysis techniques. 	<ul style="list-style-type: none"> - Markov models are memoryless i.e., the probability of a future state can only depend on the current state. - Can only be applied for analysis on systems with lifetimes that are exponentially distributed.
Monte Carlo Simulation	<ul style="list-style-type: none"> - Independence from the problem being solved. - Can be used to estimate uncertainty in models. - Results from simulations are easy to understand. - Can work with both exponential and non-exponential distributions. 	<ul style="list-style-type: none"> - Inaccuracy in dealing with very small probabilities. - Computationally expensive for practical engineering problems.

9 CONCLUSIONS AND RECOMMENDATIONS

9.1 Conclusions

The increasing complexities associated with operating in the offshore environment and the growing adoption of CBM has necessitated the development of advanced models for reliability analysis. Advanced techniques such as Petri nets (PNs) and Bayesian networks (BNs) have been demonstrated to be adept at modelling these complexities and incorporating both degradation and CBM into offshore energy systems. The overall aim of this thesis was to develop advanced reliability analytics for the analysis of critical offshore energy assets operating in dynamic conditions and under condition-based maintenance (CBM) regimes in order to improve their overall reliability as well as their operation and maintenance.

The first objective was to review existing research on the reliability of offshore energy assets focusing on the reliability of complex offshore energy systems and reliability analysis techniques. Consequently, literature reviews were conducted on the reliabilities of the subsea BOP and the offshore wind turbine, reliability analysis techniques and O&M of offshore energy assets, providing a critical discussion of the current state-of-the-art.

The second objective was to develop a framework for the implementation of CBM in complex offshore energy systems. This objective was satisfied by proposing a framework for implementing CBM based on the V-model architecture. From the proposed framework, gaps in implementation were identified and hardware, software and training requirements to close those gaps were outlined. The research was taken further by the quantification of the economic added value of implementing the CBM regime. The cost benefit analysis performed revealed through the application of the NPV and BCR techniques that CBM implementation is financially feasible. Sensitivity analyses were then performed to evaluate the effect of the discount rate on the NPV and BCR.

The third objective was to develop analytical reliability models for offshore energy assets operating under CBM in order to improve reliability allocation using

advanced reliability analysis techniques. This objective was satisfied through the development of reliability analysis models for a subsea BOP and an offshore wind turbine gearbox using the SPN and DBN techniques respectively. These models were able to incorporate the change in the asset's condition over time as well as the CBM regime. Furthermore, sensitivity analyses were performed to evaluate the effect of coverage factor and redundancy on system performance.

The fourth objective was to develop integrated models for optimising operation and maintenance of offshore energy assets. This objective was addressed through the development of O&M planning models for both the FOWT system and the OWT monopile using the SPN and DBN techniques respectively. In the FOWT system analysis, the expected number of failures, duration of downtime, and the number and cost of maintenance interventions were predicted over the lifetime of the asset. In the analysis of the OWT monopile, a model for predicting the fatigue crack growth based on continuous condition monitoring data was proposed.

The final objective was to evaluate the developed reliability and O&M models using case studies in both offshore oil and gas and wind energy. A total of four case studies were utilised to achieve this objective. These included: a subsea BOP system, a floating offshore wind turbine (FOWT) with a spar buoy floating platform, an offshore wind turbine (OWT) gearbox with an R80 configuration and an OWT monopile. Using these case studies, the models developed in this thesis have been shown to effectively analyse the reliability and O&M of offshore energy systems.

9.2 Recommendations for further research

Further studies which can be conducted based on the research performed in this thesis can be summarised as follows:

- This thesis has addressed the reliability analysis of two key offshore energy assets: the subsea BOP and offshore wind turbine (OWT). There are a number of other safety and mission-critical energy assets which degrade over time and are subject to CBM which are utilised in both the

offshore oil and gas and offshore wind sectors. The stochastic Petri net (SPN) and dynamic Bayesian network (DBN) methodologies for reliability analysis and O&M planning can be adapted and applied to other offshore energy assets.

- In chapter 3, the importance of implementing and adopting CBM in subsea BOPs was highlighted. To identify issues which can hinder CBM implementation, the application of the concept of reliability-centred maintenance (RCM) for analysing BOP component failure modes can be further investigated.
- This thesis (in chapters 4-7) explored the application of SPN and DBN techniques for reliability analysis and O&M optimisation. However, there are opportunities for exploring the application of other advanced techniques such as Markov modelling and Monte Carlo simulation for developing reliability and O&M models for complex offshore energy systems.
- Due to the unavailability of failure and maintenance data, the O&M planning study in chapter 6 does not take into account submarine cables. The model developed and deployed in this study can therefore be further extended to include power cables should these data become available.
- Given that repairs performed on faulty equipment are not often perfect (i.e., equipment goes back into service in nearly “as-good-as-new” condition), and multiple failures can occur from a single shared cause, further research could be conducted into reliability analyses and O&M planning which incorporate imperfect repairs and common-cause failures.

APPENDICES

Appendix A

A.1 Data for SPN Operation and Maintenance Analysis

In this appendix, the data for simulation of degradation and maintenance processes of FOWT components is presented. The data presented here supports the stochastic Petri net analysis in Chapter 6.

Table A.1 Type of maintenance actions adopted in floating offshore wind turbines (Le and Andrews, 2016)

Subsystem	Component	Type of Repair	Description of Repair Action
Drivetrain	Bearing	3	Pitting replacement
	Gearbox	3	Gear tooth repair
	Shaft	3	Minor repair
Hydraulic	Pump	2	Part replacement
	Valves/Pipes	3	Replacement
Braking	Callipers/Pads	2	Replace worn component
	Discs	2	Replacement
Yaw	Actuator	3	Minor repair
	Bearing	3	Corrective repair
	Brake	2	Replacement
Pitch	Actuator	3	Part replacement
	Bearing	3	Minor repair
Rotor	Hub	3	Minor corrosion repair
	Blade	4	Minor repair
Power	Generator	2	Part replacement
	Frequency Converter	1	Part/complete replacement
	Transformer	2	Part/complete replacement
Structure	Tower	4	Corrosion repair
	Nacelle	4	Crack repair
	Mooring Lines	4	Wear repair

Table A.2 Weibull distribution parameters for degradation process of floating offshore wind turbines (Hahn *et al.*, (2007) Ciang *et al.*, (2008); Le and Andrews, (2016))

Subsystem	Component	Failure rate (λ)	Degraded Condition		Critical condition		Functional failure	
			Shape	Scale (year)	Shape	Scale (year)	Shape	Scale (year)
Drivetrain	Bearing	0.0050	$\beta=1.2$	$\eta=160$	$\beta=1.5$,	$\eta=20$	$\beta=1.5$,	$\eta=20$
	Gearbox	0.0500	$\beta=1.3$	$\eta=16$	$\beta=1.2$,	$\eta=2$	$\beta=1.4$,	$\eta=2$
	Shaft	0.0050	$\beta=1.2$,	$\eta=160$	$\beta=1.5$,	$\eta=20$	$\beta=1.5$,	$\eta=20$
Hydraulic	Pump	0.0500	–		–		$\beta=1.2$,	$\eta=20$
	Valves/Pipes	0.0610	$\beta=1.2$,	$\eta=13.11$	–		$\beta=1.2$,	$\eta=3.28$
Braking	Callipers/Pads	0.0610	$\beta=1.2$,	$\eta=13.11$	–		$\beta=1.2$,	$\eta=3.28$
	Discs	0.0189	$\beta=1.2$,	$\eta=42.28$	–		$\beta=1.2$,	$\eta=10.57$
Yaw	Actuator	0.0189	$\beta=1.2$,	$\eta=42.28$	–		$\beta=1.2$,	$\eta=10.57$
	Bearing	0.0275	$\beta=1.2$,	$\eta=29.12$	$\beta=1.2$,	$\eta=3.64$	$\beta=1.2$,	$\eta=3.64$
	Brake	0.0275	$\beta=1.2$,	$\eta=29.12$	$\beta=1.2$,	$\eta=3.64$	$\beta=1.2$,	$\eta=3.64$
Pitch	Actuator	0.0275	$\beta=1.2$,	$\eta=29.12$	–		$\beta=1.2$,	$\eta=7.28$
	Bearing	0.0520	$\beta=1.2$,	$\eta=15.38$	$\beta=1.2$,	$\eta=1.92$	$\beta=1.2$,	$\eta=1.92$
Rotor	Hub	0.0520	$\beta=1.2$,	$\eta=15.38$	$\beta=1.2$,	$\eta=1.92$	$\beta=1.2$,	$\eta=1.92$
	Blade	0.0348	$\beta=1.2$,	$\eta=23.02$	$\beta=1.2$,	$\eta=2.88$	$\beta=1.2$,	$\eta=2.88$
Power	Generator	0.0520	$\beta=1.2$,	$\eta=15.38$	$\beta=1.2$,	$\eta=1.92$	$\beta=1.2$,	$\eta=1.92$
	Frequency Converter	0.0240	$\beta=1.2$,	$\eta=33.38$	–		$\beta=1.2$,	$\eta=8.35$
	Transformer	0.0670	–		–		$\beta=1.2$,	$\eta=14.93$
Structure	Tower	0.0670	–		–		$\beta=1.2$,	$\eta=14.93$
	Nacelle	0.0060	$\beta=1.2$,	$\eta=133.33$	$\beta=1.2$,	$\eta=16.67$	$\beta=1.2$,	$\eta=16.67$
	Mooring Line 1	0.0136	$\beta=1.2$,	$\eta=58.0$	$\beta=1.2$,	$\eta=7.25$	$\beta=1.2$,	$\eta=7.25$
	Mooring Line 2	0.0381	$\beta=1.2$,	$\eta=21.0$	$\beta=1.2$,	$\eta=2.63$	$\beta=1.2$,	$\eta=2.63$
	Mooring Line 3	0.0262	$\beta=1.2$,	$\eta=31.0$	$\beta=1.2$,	$\eta=3.89$	$\beta=1.2$,	$\eta=3.89$
	Anchor	0.0344	$\beta=1.2$,	$\eta=23.02$	$\beta=1.2$,	$\eta=2.88$	$\beta=1.2$,	$\eta=2.88$

Table A.3 Maintenance parameters for floating offshore wind turbines (Le and Andrews, 2016)

Maintenance type	Logistic time (hr)	Repair Time (hr)	Travel time to WT (hr)	Travel time from WT (hr)
1	160	50	1.5	1.5
2	48	10	1.5	1.5
3	24	3	1.5	1.5
4	8	3	1.5	1.5

A.2 Performance of FOWT components in the degraded state

This section presents the results for the performance of the floating offshore wind turbine components for Chapter 6.

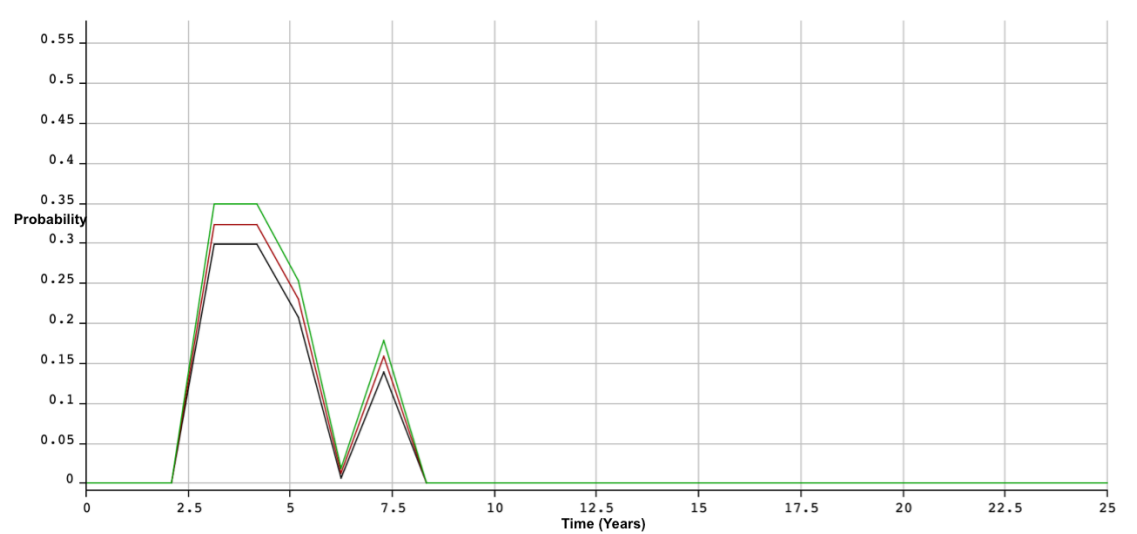


Figure A.1 The performance of drivetrain bearings in the degraded state

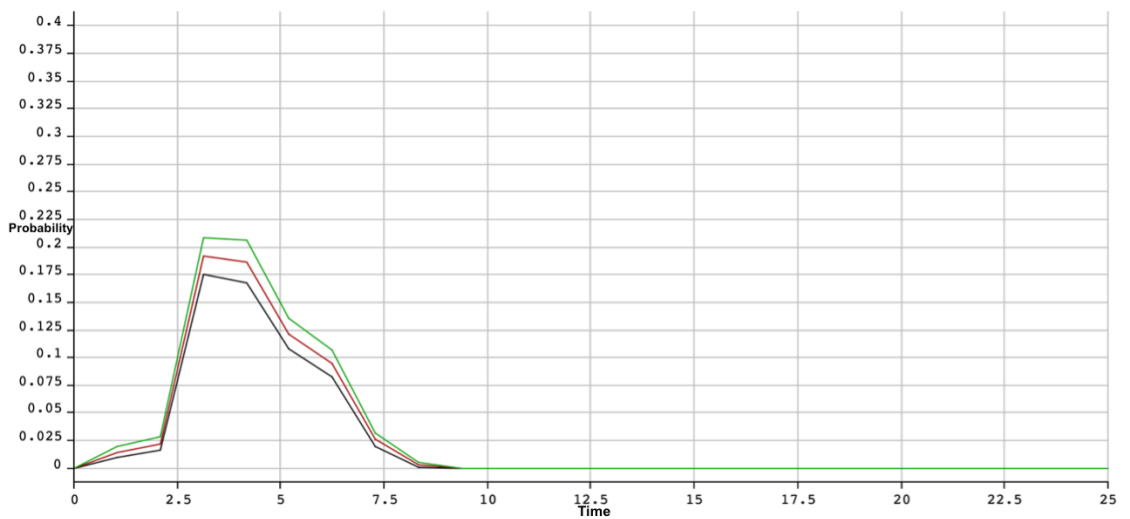


Figure A.2 The performance of the drivetrain gearing in the degraded state

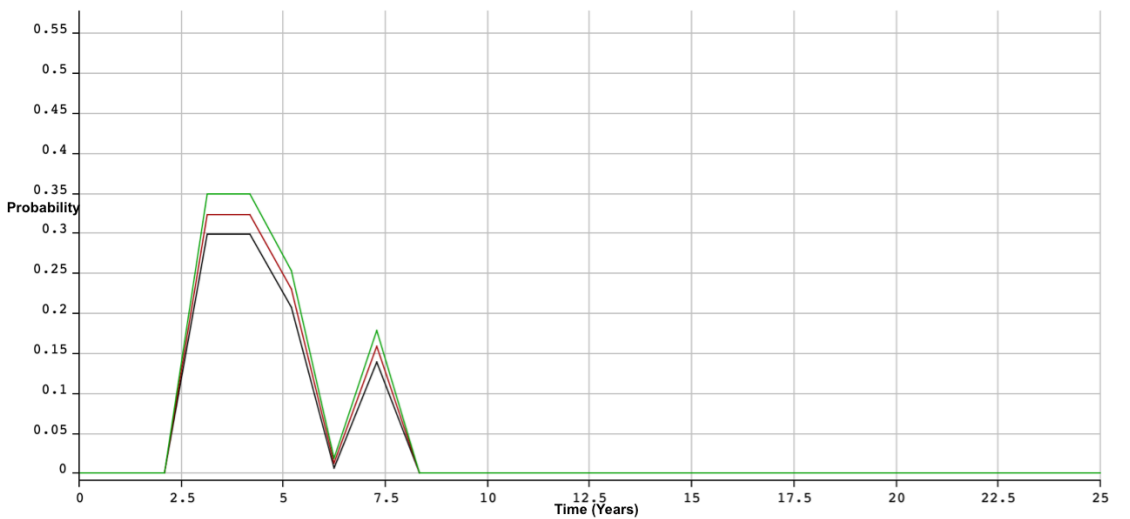


Figure A.3 The performance of the drivetrain shaft in the degraded state

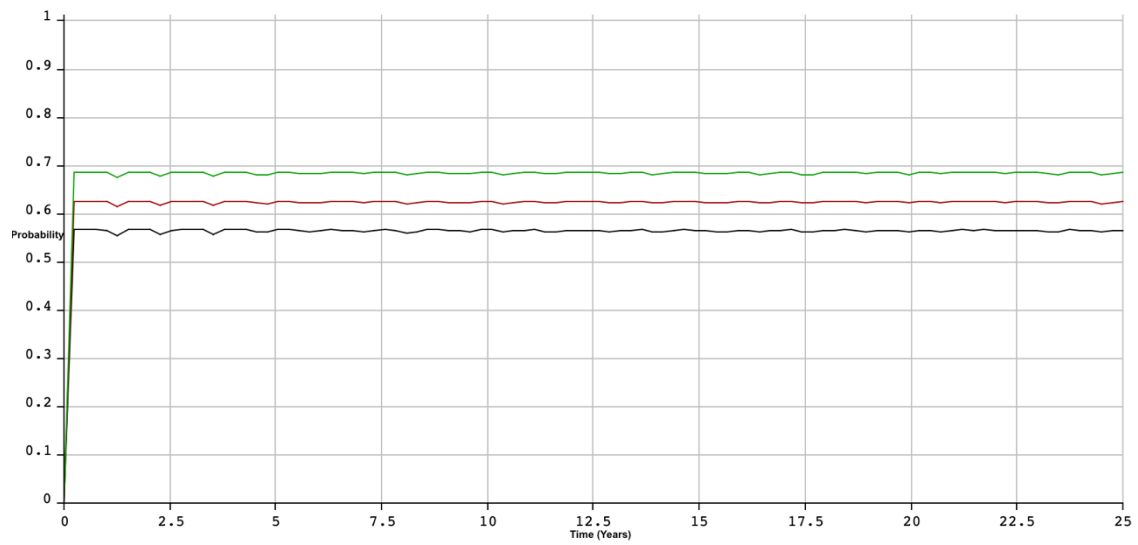


Figure A.4 The performance of the hydraulic pump in the degraded state

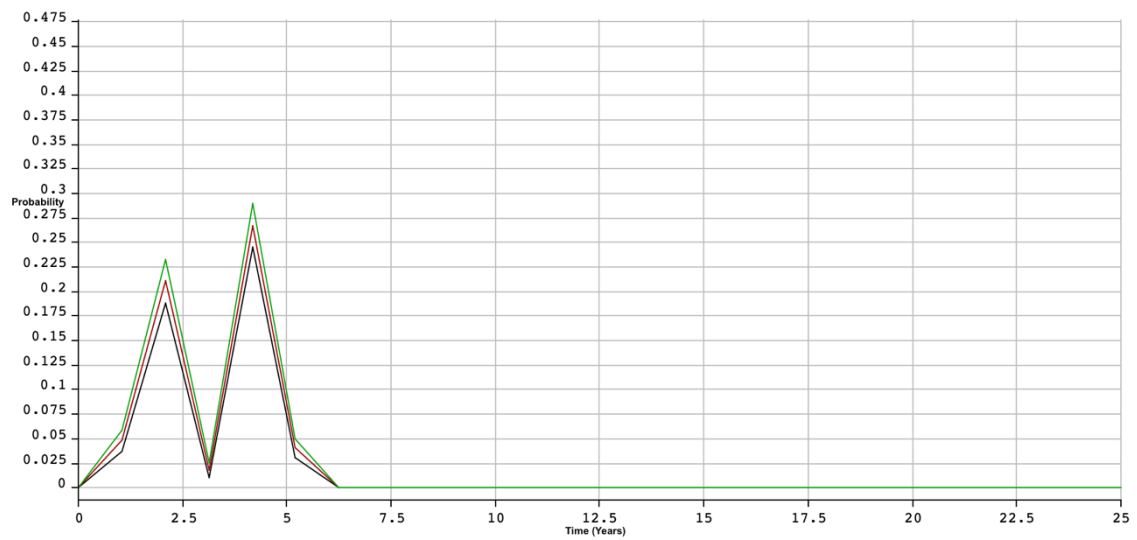


Figure A.5 The performance of the hydraulic valves in the degraded state

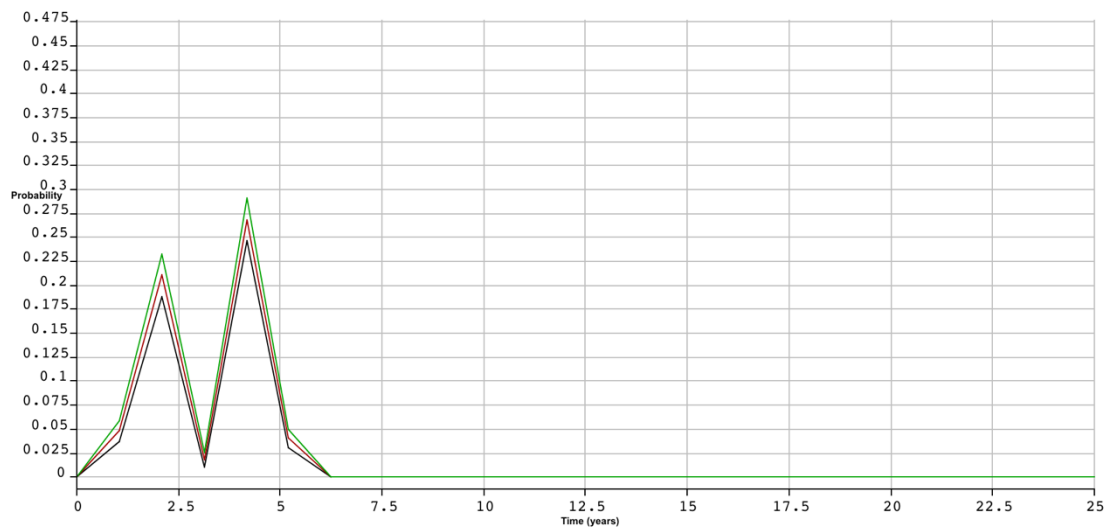


Figure A.6 The performance of the braking callipers in the degraded state

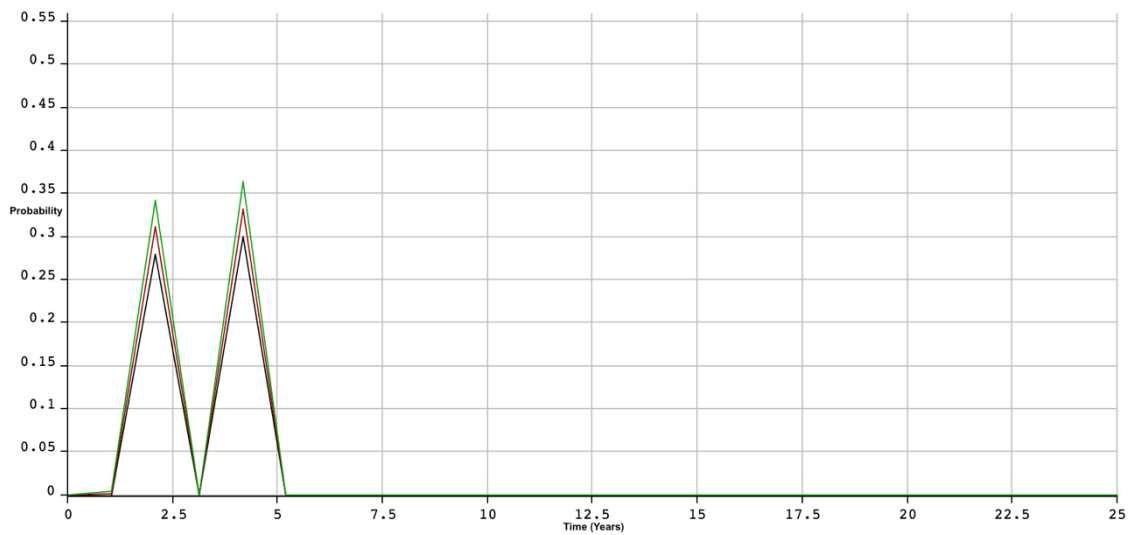


Figure A.7 The performance of the yaw actuator in the degraded state

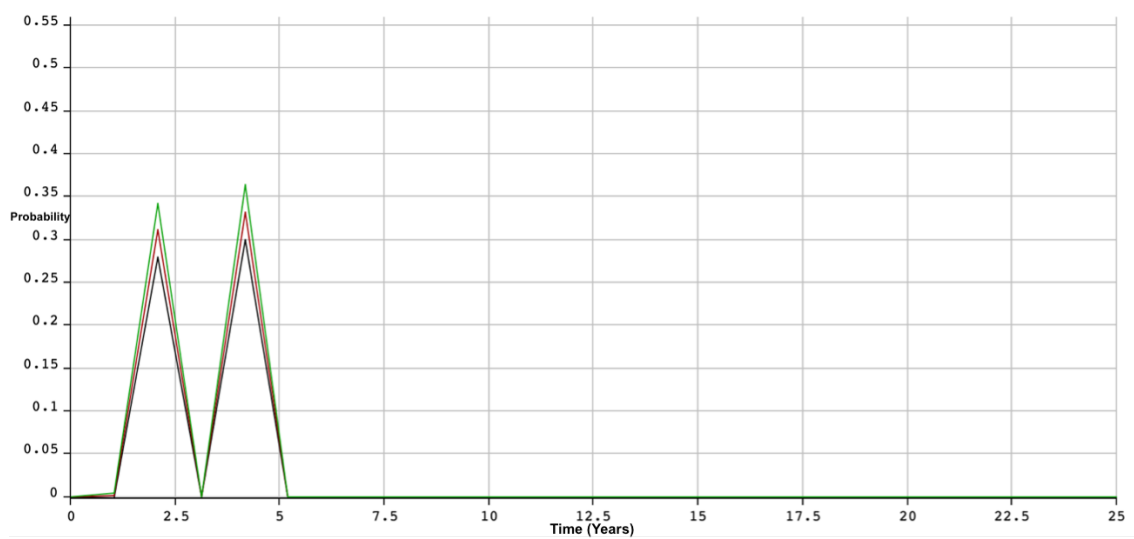


Figure A.8 The performance of the yaw bearing in the degraded state

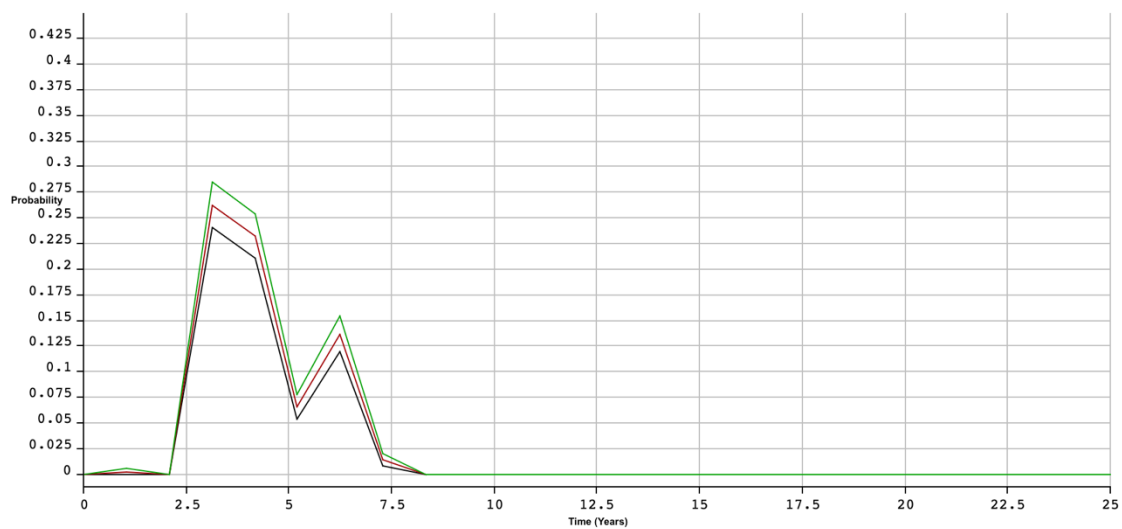


Figure A.9 The performance of the yaw brake in the degraded state

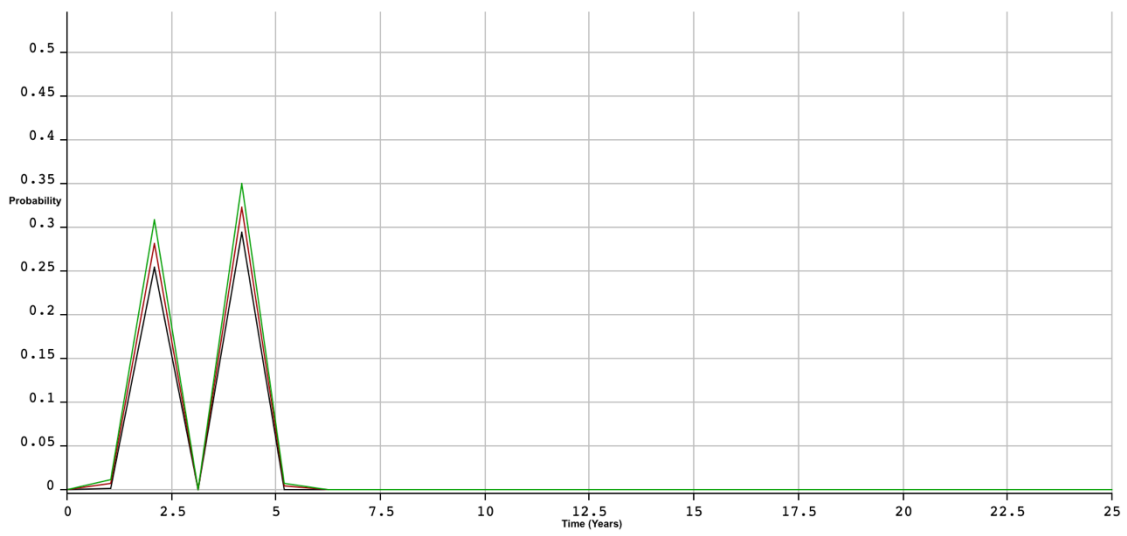


Figure A.10 The performance of the pitch actuator in the degraded state

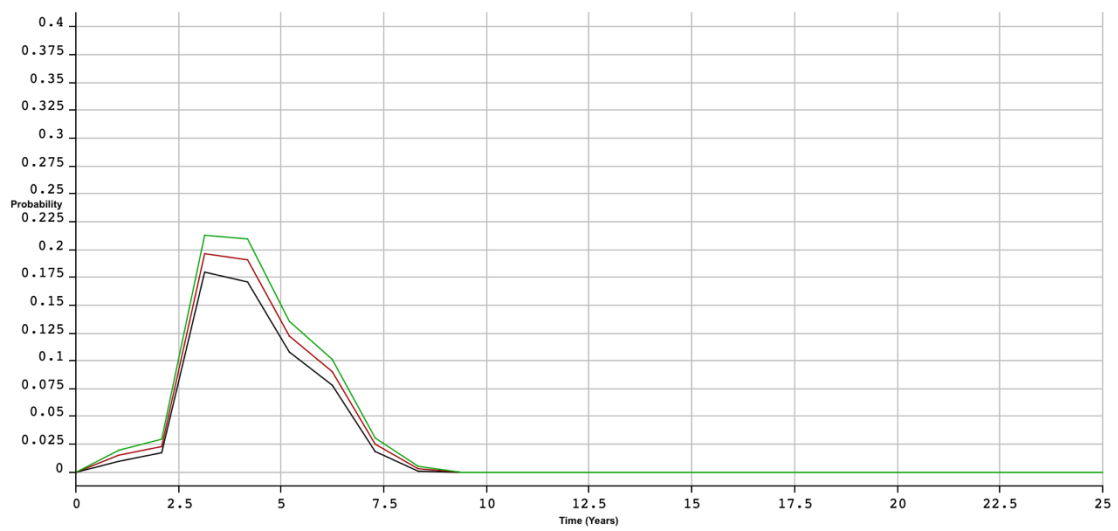


Figure A.11 The performance of the pitch bearing in the degraded state

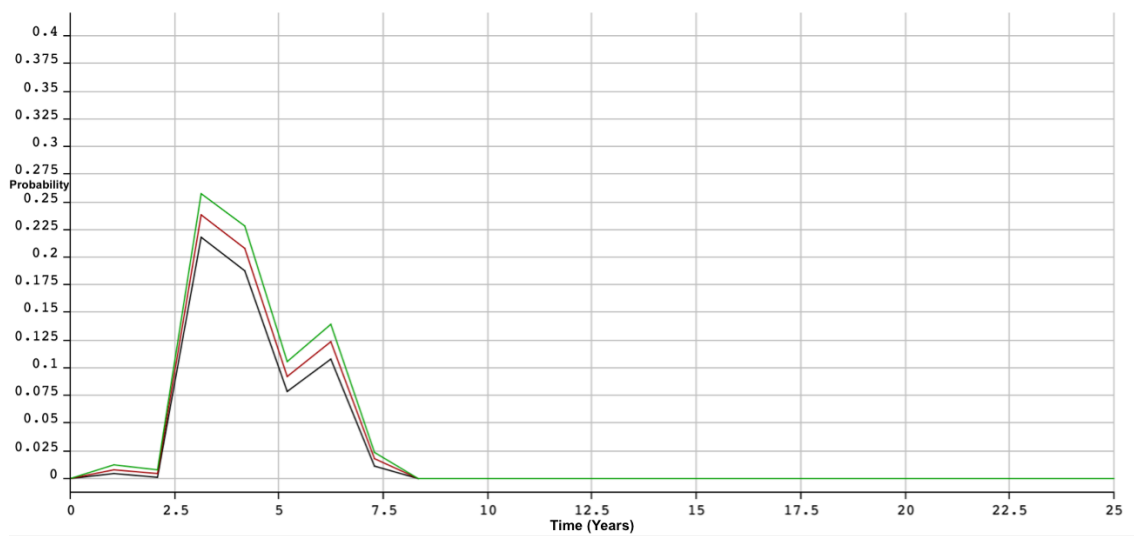


Figure A.12 The performance of the rotor hub in the degraded state

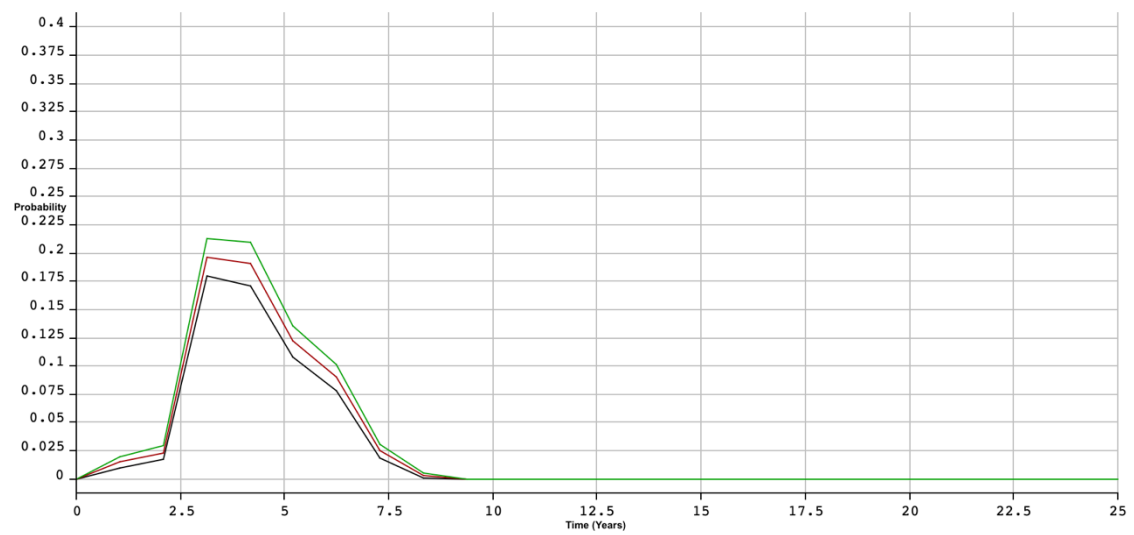


Figure A.13 The performance of the rotor blade in the degraded state

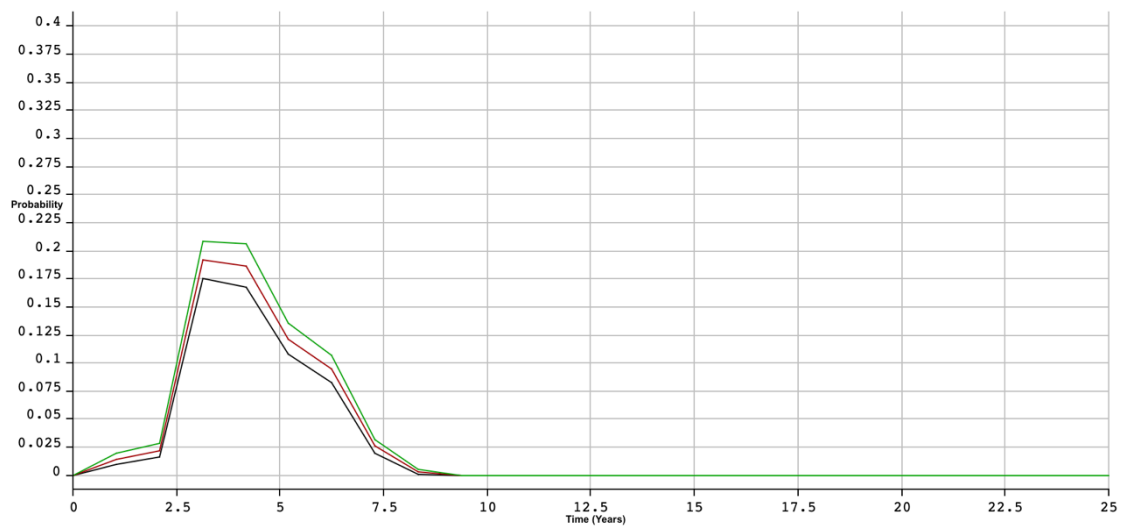


Figure A.14 The performance of the generator in the degraded state

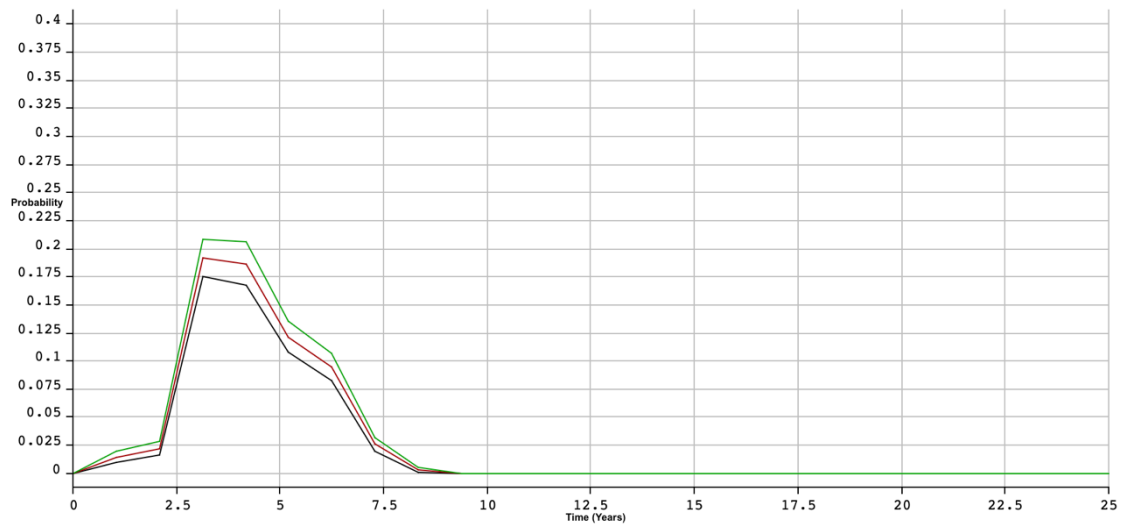


Figure A.15 The performance of the converter in the degraded state

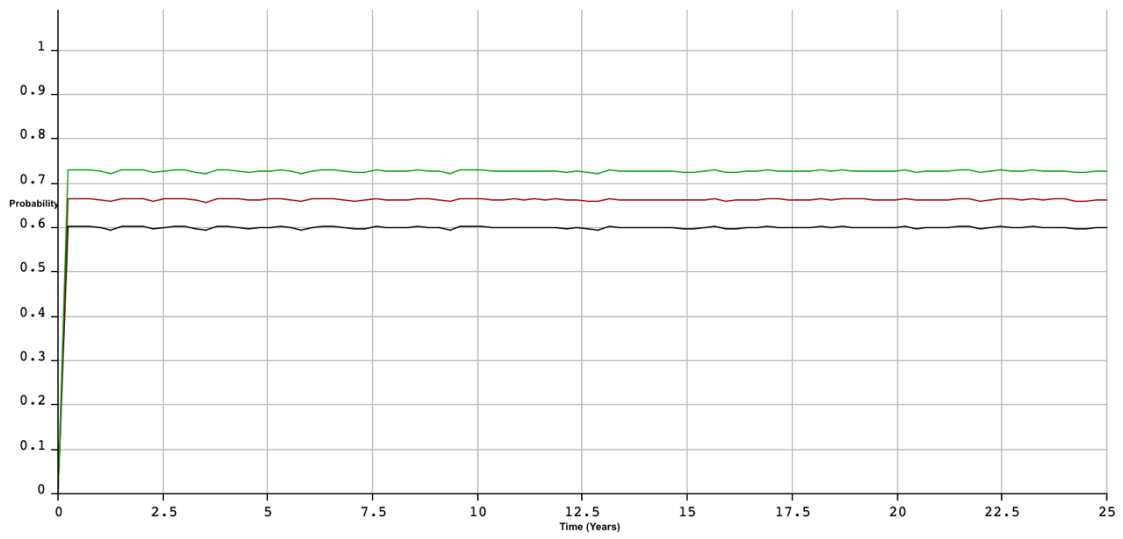


Figure A.16 The performance of the transformer in the degraded state

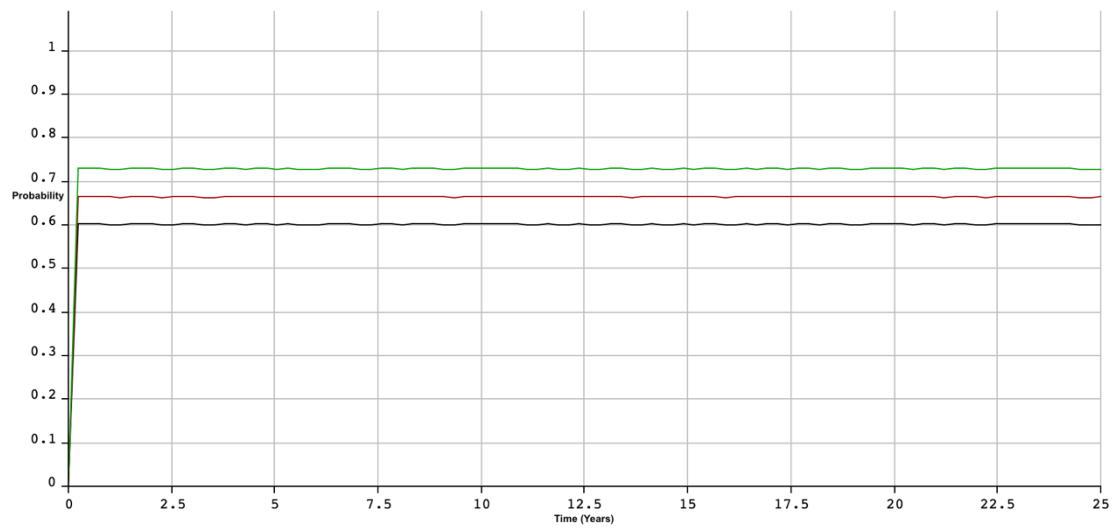


Figure A.17 The performance of the tower in the degraded state

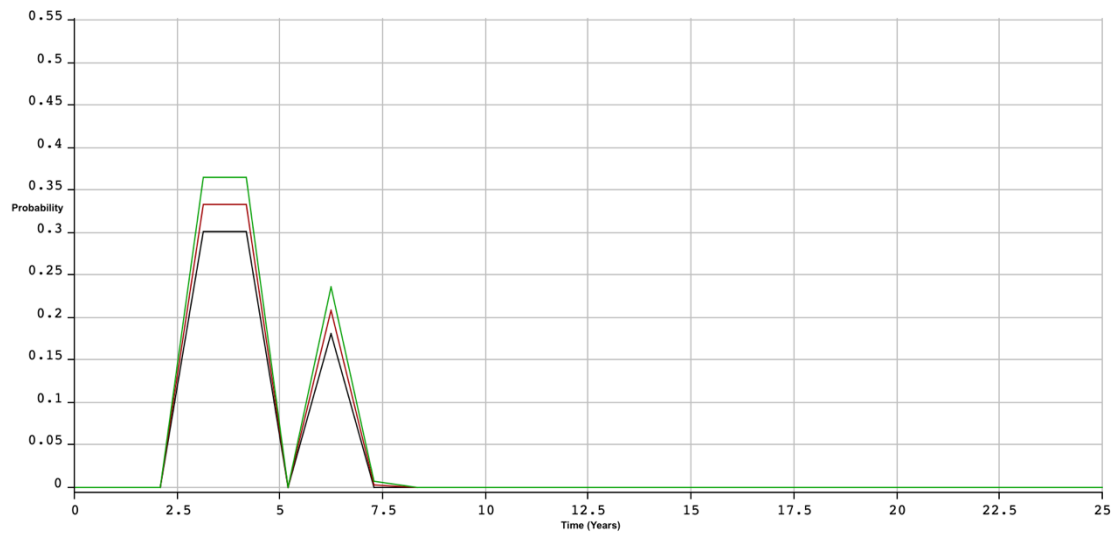


Figure A.18 The performance of the nacelle in the degraded state

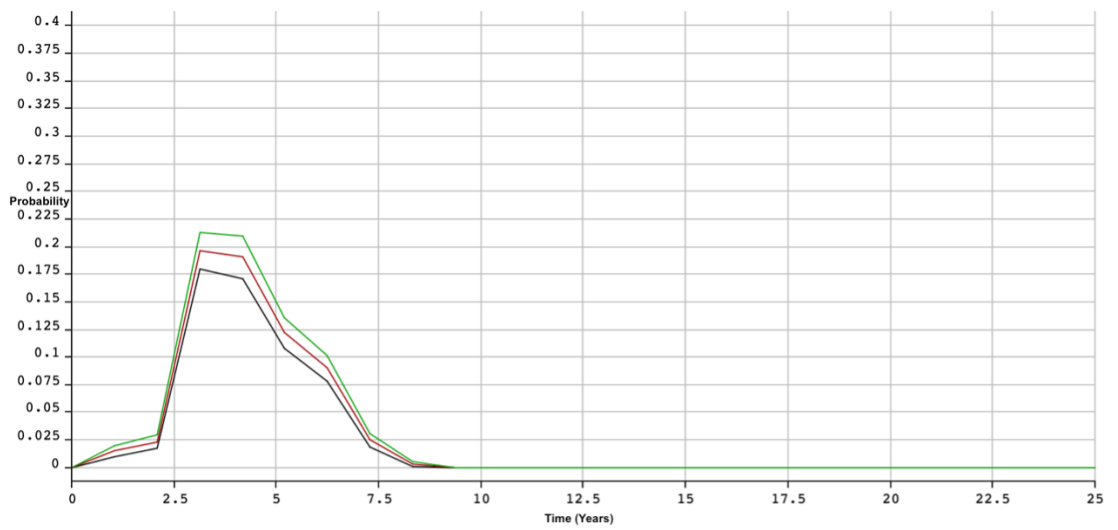


Figure A.19 The performance of the anchor in the degraded state